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Original Paper

Mobile Health Apps and Health Management Behaviors: Cost-Benefit Modeling Analysis

Rita Mano¹, DPhil

Department of Human Services, University of Haifa, Haifa, Israel

Corresponding Author:

Rita Mano, DPhil

Department of Human Services

University of Haifa

Sd. Abba Choussi 35

Mount Carmel

Haifa, 31995

Israel

Phone: 972 547611608

Email: ritamano@research.haifa.ac.il

Abstract

Background: Rising criticism about the risks associated with the use of mobile health apps necessitates a critical perspective to assess the use of these apps. A cost-benefit approach involving several moderating factors can be used to detect technology effects and individual-level push and pull factors related to health attitudes, lifestyle, and health management behaviors.

Objective: We introduce a cost-benefit perspective to examine how health attitudes related to mobile health apps and health situational factors (health crises, health changes, and hospitalization) affect the likelihood of adopting lifestyle and health management behaviors among app users.

Methods: The analysis is based on individuals' reported use of mobile health apps. The sample included 1495 US adults aged over 18 years who were contacted by landline or cellphone. A total of 50.96% (762/1495) of the participants were women. A set of logistic regression models was used to predict lifestyle and health management behaviors among users considering variations in the extent of use, health attitudes, health situation, and socioeconomic characteristics.

Results: The findings indicate that the proposed models were reasonably adequate. In all, 88.76% (1327/1495) of the cases were correctly classified regarding lifestyle behaviors, but only 71.97% (1076/1495) of the cases were correctly classified regarding health management behaviors. Although a large percentage of individuals changed their attitudes following the use of mobile health apps, only a small proportion adopted health management behaviors. The use of mobile health apps affected up to 67.95% (1016/1495) of the users for consultation and 71.97% (1076/1495) of the users for decision making. The model was effective for 88.76% (1327/1495) of the cases regarding lifestyle behaviors but only 71.97% (1076/1495) regarding health management behaviors. The moderating effect of regular use of mobile health apps significantly affects lifestyle (Wald=61.795; B=2.099; $P<.005$) but not health management behaviors (Wald=12.532; B=0.513; $P=.01$). These results collectively indicate that the use of mobile health apps for health management is partially effective.

Conclusions: The use of mobile health apps is a main route to instigate the process of health empowerment and shape health attitudes. However, an accurate assessment of the effectiveness of mobile health apps necessitates distinguishing between lifestyle and health management behaviors and adopting a cost-benefit approach because individuals facing health concerns, such as a chronic disease, health emergency, health crisis, or health change, consider their affordances and situational effects. These moderators generate a push and pull framework in the decision-making process that balances the costs and benefits of use.

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KEYWORDS

mobile health apps; health empowerment; health management behaviors; costs-benefits; mobile phone

Introduction

Background

Finding new ways to support and care for various groups of people living at home has become a challenge for health care providers [1], brought about by the growth of the aging population as well as the shortage of hospital beds [1,2]. This challenge has been partly addressed by the introduction of technology-based tools and services [2] and has led many countries to apply information technology to telemedicine care services [3]. Among these tools, mobile health apps provide general support in the areas of medical education [4], preventative health care [5], health monitoring [6], and illness management [7]. More than 100,000 mobile health apps are available on smartphones [4]. Approximately 3 to 4 billion smartphone and tablet users use mobile health apps to download and update health fitness programs, contact health care professionals, and monitor health conditions, and most users access at least one health-related app [8].

Indeed, mobile health apps play a major role in self-management and care at home. Few existing studies have explored the variations in using mobile phones for health-related issues while on the go, and some studies have begun to report user feedback on specific apps [1], mostly showing that these technological advances [2] have enabled better health care services to be provided to the public [9]. Not surprisingly, mobile health apps attract the attention of institutional health care providers [8,10] for various purposes, such as improving treatment, diagnosing early symptoms, providing faster responses, accessing medical data and decision support systems, increasing digital health literacy, and accentuating support on social platforms [11].

Many studies have assessed the feasibility, functionality, clinical utility, benefits, and risks of mobile health apps [12-16]. Evidence indicates that mobile health apps are effective in providing feedback and improving goal setting and self-monitoring in eating disorders [17], alcohol use disorders [18], and attempts to stop smoking [19]. They are also used to encourage physical activity [20] and provide psychotherapy [15]. The demand for home care services has grown over the last decades [9,21] to support individuals and diverse groups [2], including the aging and chronically ill people [11], to better manage their health at home [4]. However, some of these studies have also indicated that the focus on specific groups led to a missed opportunity to address how users facing health-related emergencies put off further use of mobile health apps [21-25].

First, technology skills vary [26], as do the purposes and extent of technology use [27,28]. Second, health management behaviors involve different levels of uncertainty and vulnerability [28] or perceived threats [29,30]. Third, health attitudes do not necessarily coincide with health management behaviors [31], as issues of functionality may not necessarily lead to lifestyle and health management behaviors [32]. Finally, sociodemographic variations are important when considering both the use of mobile health apps and health management behaviors [33,34]. This is why we need to distinguish between lifestyle health management behaviors, such as increasing daily vitamin intake and engaging in a physical fitness program, and

more complex health care management behaviors, such as those related to the management of serious health concerns [12,35] considering the different needs and affordances of individuals.

In this study, we address these concerns. We consider the possibility that even though mobile apps are highly accessible and exert a general beneficial effect on health attitudes and empowerment, their potential to encourage health management behaviors is limited due to the limited consideration of individual health situations and affordances. We examine how variations in the use of mobile health apps enhance or restrain the adoption of lifestyle and health management behaviors among individuals experiencing health concerns [9,11,34] and health crises.

The shift from *mechanical to informational* medicine [36] has placed a growing responsibility on individuals regarding health concerns [37] and urged them to increase their own health awareness through access to web-based health information [38] and health services [39]. Mobile health apps increase health awareness and instigate health management behaviors by causing individuals to adhere to new health routines and improve existing ones [40]. Three major theoretical directions enable an integrative approach: (1) technology-human interaction models, (2) health empowerment (HE) and health belief model (HBM), and (3) the social diversification hypothesis (SDH) [33].

Technology-Human Interaction Models

The technology acceptance model (TAM) [41] focuses on factors associated with the use of internet communication technology (ICT). TAM assumes that variations in the acceptance of computerized technology reflect a set of facilitating conditions, including expected effort, performance, and social influence [42,43]. TAM suggests that individuals will adopt technology when its perceived usefulness and perceived ease of use are high, and ICT use is likely to shape a new set of attitudes regarding technology's potential to contribute to health purposes [44,45]. The *perceived functionality* of mobile health apps will increase the level of use of the mobile health apps and the need to update such apps [46]. Health adoption models test these assumptions.

The HE and HBM Perspective

The HE perspective introduced the notion of health efficacy and the right to express health aspirations, thus enabling individuals to develop critical awareness about their existing health conditions [47-49]. The HE model complements assumptions from communications and computer-mediated models and provides specific hypotheses about the effect of individual health-related conditions on health changes. Individuals who learn and internalize aspects of health and disease and develop health-related consciousness are more likely to express health-related aspirations and expectations, and these individuals develop the confidence to adhere to a more focused approach to health concerns, making them more willing to use mobile health apps [50]. Moreover, a rational consumer choice approach will motivate individuals to seek even more information and compare multiple sources of information before making health decisions [49].

HBM applies the concepts of self-efficacy and HE. Initially, HBM suggested that beliefs and attitudes moderate the impact of technology on health management behaviors among individuals concerned with health issues [51]. Later, HBM focused on the perceived benefits or barriers stemming from taking action to prevent diseases or disorders [28]. The relative weight of benefits versus barriers affects the likelihood of taking preventive action. When barriers are perceived to be high, individuals are less likely to engage in healthy lifestyle behaviors [52]. HBM was applied to predict helmet use [53], improve driving [27], improve adherence to treatment [28], and improve communication about health concerns [44]. Both HE and HBM suggest that individuals will be more willing to play an active role in preventing, treating, and following up on health issues for themselves and others [49,54]. Hence, we hypothesize the following:

- *H1*: Greater use of mobile health apps will increase the likelihood of a change in approach when addressing a health concern.
- *H2*: Greater use of mobile health apps will increase the likelihood of making a decision to address a health concern.
- *H3*: Greater use of mobile health apps will increase the likelihood of asking a health provider new questions or seeking a second opinion from another doctor.

Nonetheless, neither the HE nor the HBM model provides the necessary assumptions to tap into factors associated with choices and behaviors when individuals face a set of health-related situations.

The SDH Perspective

SDH addresses the possible outcomes of inequalities in the use of ICT devices on additional aspects of life, such as health [55]. ICT devices serve as a major vehicle for overcoming environmental barriers, both geographic and temporal. Nevertheless, their use is often affected by the (1) costs involved in the acquisition and use of ICT and mobile devices [56]; (2) technology skills necessary to use such devices [57]; (3) individuals' beliefs, attitudes, goals, and plans; and (4) differences in their socioeconomic background [58]. These socioeconomic characteristics, including age, gender, ethnic background, education, and income, are proxies for the potential to (1) use and (2) apply technology devices [33,55]. Similarly, recent studies indicate that aging individuals are less likely and women are more likely to use and capitalize on technology to adopt lifestyle and health management behaviors [34]. Hence, we hypothesize the following:

- *H4*: Greater use of mobile health apps will increase the likelihood of adopting lifestyle health management behaviors after controlling for variations in socioeconomic factors and health attitudes.
- *H5*: Greater use of mobile health apps will increase the likelihood of adopting health management behaviors after controlling for variations in socioeconomic factors and health attitudes.

Mobile health apps may inspire individuals to reshape their health attitudes. Nonetheless, individuals may also *critically* evaluate the functionality of mobile health apps and dismiss the

use of mobile health app guidelines and programs [49,54]. A perceived threat that might otherwise motivate individuals to adopt lifestyle health management behaviors [30,44] may cause individuals to restrain from the use and influence of mobile health apps [59].

Health Behaviors: The Concept of Affordances

Overall, the HE and HBM models [60], and to some extent SDH [33], assume that rational health management behaviors emerge when individuals develop empowering attitudes regarding a health concern. However, these assumptions are based on shaky ground. First, individuals may not necessarily behave rationally, especially when many additional factors come into play. Second, individuals are more likely to capitalize on virtual health information regarding lifestyle but not on health management [59]. To clarify these points, we addressed the role of affordances [61] in health management behaviors.

The concept of *affordance* captures the beneficial or injurious aspect of objects and is relative in terms of how well objects fit an individual situation. The strength of affordances lies in the individual's perceptions regarding the need to weigh one's action *possibilities* [62]. The term *affordances* denotes the need to address everyday objects together with their features and functions. Individuals using a device are seldom preoccupied with its objective qualities because these objective features and functions do not necessarily fit users' needs. A lack of fit shapes individuals' perceived affordances and generates the need to assess the costs and benefits of using apps. As a result, individuals use a push and pull framework in their decision-making process before acting on the content of the ICT medium [34]. A set of personal situations may encourage or discourage individuals from developing favorable health attitudes and adopting health management behaviors. Hence, we hypothesize the following:

- *H6*: Greater use of mobile health apps will increase the likelihood of lifestyle behaviors after controlling for variations in mobile health app use and health attitudes.
- *H7*: Greater use of mobile health apps will increase the likelihood of health management behaviors after controlling for variations in mobile health app use and health attitudes.

Technology devices such as mobile health apps are reported to fall short of their intended purposes [63-65] because, in practical terms, individuals assess their situation and apply a push and pull decision-making process [66].

The Push and Pull Perspective: A Situational Approach to Health Behavior

The push-pull perspective analyzes the migration decisions [66]. It highlights the need to identify the best *destination* option during migration while considering a set of factors that may *threaten* the outcome of the migration. Favorable conditions *push* individuals in a specific direction toward a specific location, whereas less favorable conditions *pull* them away. By applying the push-pull perspective in health, we can assume that individuals' health management behaviors depend on the way they relate to their specific health situation, especially when it involves a perceived threat or risk [15,44]. In the process, users will consider adopting mobile health apps according to

their specific situation regarding a health concern, especially when it manifests in a medical emergency or an unexpected health change. This *situational* health context will ultimately shape their perceived affordances regarding the use of mobile health apps and affect their health management behaviors [62,67,68]. Individuals may then consider their affordances in terms of the potential of mobile health apps to support their needs in light of their situation. When these affordances are costly, individuals may not be willing to use mobile health apps, especially individuals diagnosed with a chronic condition [39]. Hence, we hypothesize the following:

- *H8*: Use of mobile health apps will increase the likelihood of lifestyle behaviors after controlling for situational effects.
- *H9*: Use of mobile health apps will increase the likelihood of health management behaviors after controlling for situational effects.

Objectives

This study aimed to investigate the variations in health attitudes and behaviors of individuals using mobile health apps. We conducted an analysis of smartphone users to explore the extent to which the use of mobile health apps enhances or restrains the adoption of health management behaviors among individuals experiencing different situational health concerns. We address their existing experiences of using health-related smartphone apps and their health management behaviors following the currently available or future apps. We sought to determine the extent of use and behaviors relevant to lifestyle and health management. We also considered that a set of moderating push and pull factors, including the diagnosis of medical health and the occurrence of a health emergency crisis, may lead to disinclination to use the apps.

Methods

Sample

This study draws on a secondary analysis of the data released by Princeton [69]. The sample was taken from a national tracking survey of 8323 individuals aged over 18 years and contacted by landline or cellphone. The analysis is based on individuals' reported use of mobile health apps (N=1495). The sample comprised 50.96% (762/1495) women; 60.6% (921/1354) were married or cohabitating, 41.33% (618/1495) were parents of children living at home, 29.69% (444/1495) had less than a college degree, and 24.15% (361/1495) earned less than US \$30,000. A total of 79.66% (1191/1495) of the sample reported using a single health app, and 20.06% (300/1495) of the sample reported using more than one app (Multimedia Appendix 1).

Dependent Variables

Health Behaviors

Health behaviors manifest in two different ways: (1) lifestyle behavior: do you currently keep track of your own weight, diet, or exercise routine? (1=yes) and (2) health management behavior: do you happen to track your own blood pressure, blood sugar, sleep patterns, headaches, or any other indicator? (1=yes).

Health Attitudes

The use of mobile health apps influenced the following: (1) approach: has tracking this health indicator changed your overall approach to maintaining your health or the health of someone you help take care of? (1=yes), (2) decision making: has tracking this health indicator affected a decision about how to treat an illness or condition? (1=yes), and (3) consulting: has the use of mobile health apps led you to ask a doctor new questions or to seek a second opinion from another doctor (1=yes).

Independent Variables

The independent variables refer to the use of mobile health apps: (1) number of apps used: what kind of health apps do you currently have on your phone? Respondents replied to the question 10 times for 10 uses. We used the first 4 counts reporting 4 different types of health concerns. The range is from only one use to four uses, (2) updates (1=yes), and (3) update frequency (1=every day).

Control Variables

Socioeconomic Characteristics

An important role to the use of apps for health purposes is the role assigned to socioeconomic variations. There are 5 key variables, which have been described below.

Age

Age is a proxy for technology skills and the likelihood of chronic illness (18-85 years). Studies have shown that older individuals perform more poorly than young people in using internet browsers, finding search engines, and navigating the internet [57]. Older people often experience more difficulties using technology than younger people [33], which may affect both use and outcomes among older age groups [70,71]. Moreover, health usually deteriorates with age [72], so age may be an important motivation for seeking health-related information and engaging in health-related discussions [73].

Gender

Consistent findings indicate that women use the internet for health purposes more than men do [33,34], reflecting their social function of family caregivers [33] and health managers [74]. Men were also found to have lower odds of using health sites and web-based consultations [75] (1=male).

Marital Status

Married or cohabitating individuals are reported to be more likely to use web-based health services [59] and consult web-based rankings or reviews [75] (1=yes).

Education

Education increases the likelihood of health literacy and the ability to understand medical information, including drug prescriptions, the etiology of diseases, and risks. Better cognitive skills, attributed to highly educated individuals, lead to a better evaluation of health information [59]. Therefore, more educated individuals may want to use technology for health-related concerns more than less educated individuals (ranging from 1=no formal education to 10=PhD).

Income

How much did you earn last year? Studies on inequalities in the use of web-based health information have found differences between groups based on their socioeconomic status. The likelihood of searching for web-based health information was inversely associated with income (ranging from 1=less than US \$10,000 to 6=less than US \$150,000).

Situational Effects

Individuals' health management includes several specific conditions that may affect the use of apps for health purposes: (1) chronic disease: previous studies have shown that those who report having a chronic illness are more likely to seek medical information and participate in online health-related forums [40,67]; (2) health crisis: in the last 12 months, have you personally faced a serious medical emergency or crisis (1=yes); (3) health emergency: in the last 12 months, have you personally gone to the emergency room or have been hospitalized unexpectedly (1=yes); and (4) health change: in the last 12

months, have you personally experienced any significant change in your physical health, such as gaining or losing a lot of weight, becoming pregnant, or quitting smoking (1=yes).

Strategy Analysis

To examine the effect of technology use on (1) health attitudes and (2) health management behaviors, we implemented the following steps.

First, we provide a general description of the distribution of the sample across the study variables ([Multimedia Appendix 1](#)).

Second, we tap into an overall estimation of the impact of the model's independent and control variables on the dependent variable (health attitudes following the use of mobile health apps) using the classification tables of a logistic regression procedure. We estimate the correctly classified cases, which cover both successful and failed cases. We present the results separately for the effects of mobile health app use on health attitudes ([Table 1](#)) and on lifestyle and health management behaviors ([Table 2](#)).

Table 1. Logistic regression summary models predicting the number of correctly classified cases for the model that predicts the influence of mobile health apps on health attitudes.

| Observed effects | Participants | | |
|-----------------------------------|-------------------------------------|------|---|
| | Number of correctly predicted cases | | Percentage of correctly predicted cases |
| | False | True | |
| Influenced health approach | | | |
| False | 377 | 294 | 56.2 |
| True | 182 | 638 | 77.8 |
| Overall percentage | N/A ^a | N/A | 68.1 |
| Influenced health decision | | | |
| False | 844 | 98 | 89.6 |
| True | 321 | 228 | 41.6 |
| Overall fit | N/A | N/A | 71.9 |
| Influenced consulting | | | |
| False | 761 | 145 | 84.0 |
| True | 334 | 252 | 43.0 |
| Overall fit | N/A | N/A | 67.9 |

^aN/A: not applicable.

Table 2. Logistic regression summary models and percentage of correctly classified cases predicting likelihood of lifestyle and health management behaviors following the use of mobile health apps.

| Observed effects | Participants | | Percentage of correctly predicted cases |
|-----------------------------------|-------------------------------------|------|---|
| | Number of correctly predicted cases | | |
| | False | True | |
| Lifestyle behavior | | | |
| False | 132 | 107 | 55.2 |
| True | 60 | 1192 | 95.2 |
| Overall fit | N/A ^a | N/A | 88.8 |
| Health management behavior | | | |
| False | 807 | 145 | 84.8 |
| True | 273 | 267 | 49.4 |
| Overall fit | N/A | N/A | 72.0 |

^aN/A: not applicable.

Third, we explored the direct impact of mobile health apps' use on lifestyle and health management behaviors by using logistic regression. To this end, we proceeded systematically. First, we introduced the set of variations in mobile health apps' use (number of mobile health apps and update frequency). Second, we added the impact of variations in health attitudes following

mobile health apps' use. Subsequently, we inserted socioeconomic effects and situational effects. This hierarchical systematic method enables us to assess the extent to which variables in each set of predictors increase or decrease the likelihood of predicting lifestyles (Table 3) and health management behaviors (Table 4).

Table 3. Logistic regression coefficients predicting health attitudes following the use of mobile health apps.

| Variables affecting health attitudes | B | SE | Wald | Significance (<i>P</i> value) | Explained (B) |
|--|---------------------|-------|---------|--------------------------------|---------------|
| Approach regarding a health concern | | | | | |
| Mobile health apps' use | | | | | |
| Number of health apps = -1 | -0.448 ^a | 0.112 | 16.046 | <.001 | 0.639 |
| Number of health apps = +1 | 0.247 | 0.174 | 2.006 | .16 | 1.280 |
| Updates frequency | 1.40 ^a | 0.128 | 120.447 | <.001 | 4.054 |
| Socioeconomic factors | | | | | |
| Sex: 1=male | 0.000 | 0.006 | 0.004 | .95 | 1.000 |
| Married or cohabitation | 0.772 ^a | 0.126 | 37.351 | <.001 | 2.163 |
| Parenthood | 0.034 | 0.035 | 0.961 | .33 | 1.035 |
| Education | 0.048 | 0.152 | 0.099 | .75 | 1.049 |
| Income | -0.155 ^a | 0.037 | 17.252 | <.001 | 0.857 |
| Decision regarding a health concern | | | | | |
| Mobile health apps' use | | | | | |
| Number of health apps = -1 | -0.801 ^a | 0.138 | 33.804 | <.001 | 0.449 |
| Number of health apps = +1 | 0.794 ^a | 0.170 | 21.787 | <.001 | 2.212 |
| Updates frequency | -0.164 | 0.127 | 1.664 | .197 | 0.849 |
| Socioeconomic factors | | | | | |
| Sex: 1=male | 0.009 | 0.006 | 2.420 | .12 | 1.010 |
| Married or cohabitation | 0.417 ^a | 0.128 | 10.562 | .001 | 1.518 |
| Parenthood | 0.054 | 0.036 | 2.253 | .13 | 1.055 |
| Education | 0.232 | 0.157 | 2.184 | .14 | 1.261 |
| Income | -0.120 ^a | 0.039 | 9.749 | .002 | 0.887 |
| Consulting regarding a health concern | | | | | |
| Mobile health apps' use | | | | | |
| Number of health apps = -1 | 0.197 | 0.112 | 3.071 | .08 | 1.217 |
| Number of health apps = +1 | 1.749 ^a | 0.174 | 100.893 | <.001 | 5.748 |
| Updates frequency | -0.348 ^a | 0.125 | 7.762 | .005 | 0.706 |
| Socioeconomic factors | | | | | |
| Sex: 1=male | -0.008 | 0.006 | 1.580 | .21 | 0.992 |
| Married or cohabitation | -0.195 | 0.126 | 2.381 | .12 | 0.823 |
| Parenthood | 0.056 | 0.035 | 2.589 | .11 | 1.058 |
| Education | -0.048 | 0.156 | 0.094 | .76 | 0.953 |
| Income | -0.142 ^a | 0.038 | 14.036 | <.001 | 0.867 |

^a*P*<.001.

Table 4. Logistic regression coefficients predicting lifestyle and health management behaviors following the use of mobile health apps.

| Characteristics | Lifestyle behavior | | | | | Health management behavior | | | | |
|------------------------------|----------------------|-------|--------|-------------------------|---------------|----------------------------|-------|--------|-------------------------|---------------|
| | B | SE | Wald | Significance (P values) | Explained (B) | B | SE | Wald | Significance (P values) | Explained (B) |
| Mobile health app use | | | | | | | | | | |
| Number of mobile apps = -1 | -0.863 ^a | 0.187 | 21.295 | <.001 | 0.422 | 0.220 | 0.124 | 3.154 | .08 | 1.246 |
| Number of mobile apps = +1 | -1.827 ^a | 0.330 | 30.725 | <.001 | 0.161 | 0.042 | 0.200 | 0.044 | .83 | 1.043 |
| Frequency of updates | 2.099 ^a | 0.267 | 61.795 | <.001 | 8.162 | 0.513 | 0.145 | 12.532 | <.001 | 1.670 |
| Health attitudes | | | | | | | | | | |
| Approach | 1.493 ^a | 0.263 | 32.110 | <.001 | 4.450 | 0.230 | 0.155 | 2.189 | .14 | 1.258 |
| Decision | 0.865 ^a | 0.283 | 9.333 | .002 | 2.374 | 0.914 | 0.155 | 34.915 | <.001 | 2.494 |
| Consulting | 2.713 ^a | 0.322 | 70.820 | <.001 | 15.07 | 0.481 | 0.154 | 9.796 | .002 | 1.618 |
| Socioeconomic effects | | | | | | | | | | |
| Age | -0.070 ^a | 0.011 | 44.445 | <.001 | 0.932 | 0.042 | 0.007 | 35.855 | <.001 | 1.043 |
| Sex: 1=male | -0.1736 ^a | 0.244 | 50.567 | <.001 | 0.176 | -0.406 | 0.143 | 8.094 | .004 | 0.666 |
| Married: 1=yes | -0.043 | 0.060 | 0.516 | .47 | 0.958 | 0.238 | 0.039 | 36.962 | <.001 | 1.269 |
| Parent: 1=yes | -0.144 | 0.250 | 0.332 | .56 | 0.866 | 0.595 | 0.171 | 12.175 | <.001 | 1.813 |
| Education | 0.641 ^a | 0.069 | 85.811 | <.001 | 1.898 | -0.094 | 0.042 | 4.944 | .03 | 0.911 |
| Income | 0.002 | 0.003 | 0.290 | .59 | 1.002 | 0.002 | 0.002 | 0.618 | .43 | 1.002 |
| Situational effects | | | | | | | | | | |
| Chronic disease | -1.35 ^a | 0.239 | 32.221 | <.001 | 0.257 | 1.007 | 0.142 | 50.471 | <.001 | 2.737 |
| Emergency | -1.842 ^a | 0.602 | 9.367 | .002 | 6.312 | -1.012 | 0.280 | 13.101 | <.001 | 0.363 |
| Health crisis | -0.751 ^a | 0.343 | 4.795 | .03 | 0.472 | 1.086 | 0.208 | 27.256 | <.001 | 2.962 |
| Health change | -0.699 ^a | 0.254 | 7.583 | .006 | 0.497 | -0.679 | 0.168 | 16.290 | <.001 | 0.507 |

^a $P < .001$.

Results

Testing the Overall Fit of a Push and Pull Model in Predicting Health Attitudes and Health Behaviors

First, we tested how well the proposed model enabled us to correctly classify the examined cases. The findings indicate that the proposed models are reasonably adequate and make it possible to classify the examined cases correctly for health attitudes (up to 1076/1495, 71.97%) following the use of apps. The overall percentage of correctly predicted cases indicates that the use of mobile health apps affects up to 67.95% (1016/1495) individuals for consultation and 71.97% (1076/1495) for decision making. The model was effective for 88.76% (1327/1495) of the cases regarding lifestyle behaviors but only for 71.97% (1076/1495) of the cases regarding health management behaviors.

A closer look at the positive outcomes shows that a higher level of involvement in the reaction, which ranged from a mere attitude to a practical behavior, decreased the effectiveness of

mobile health apps. Although a large percentage of individuals (1163/1495, 77.79%) changed their attitudes following the use of mobile health apps, only a small proportion (738/1495, 49.36%) used them for health management behaviors and even less (642/1495, 42.94%) sought out a second opinion. Therefore, the results indicate that using mobile health apps is generally less effective in generating higher HE than expected, especially after considering situational effects.

Mobile Health Apps and Health Attitudes

Extent of Use

The findings in Table 3 suggest that an increase in mobile health apps' use does not have a uniform effect on health-related attitudes. In addition, the number of apps used is likely to have both positive and negative effects. For example, although the use of a limited number of mobile health apps can decrease the likelihood of changing the user's approach (Wald=16.046; B=-0.448), only the use of more than one app increases the likelihood of taking steps to seek further consultation

(Wald=100.893; B=1.749) as well as to make a decision (Wald=21.787; B=0.794).

Updates

Similarly, an increase in the frequency of updates can increase the likelihood of changing a user's approach (Wald=120.447; B=1.4), but it can also decrease the likelihood of seeking further consultations from a health provider (Wald=7.762; B=-0.348). Individuals with specific health concerns are more likely to crosscheck information or look for multiple health concerns. These results clearly point to the possibility of distress following the excessive use of mobile health apps in terms of information overload, similar to the technology fatigue syndrome already apparent in the use of email-based communication and the differential effects of digital communication on individuals' well-being [76]. To explore the source of these differences and in line with SDH [33], we next examined socioeconomic effects.

Socioeconomic Effects

The most impressive findings among the socioeconomic effects are the negative effects of income level and marital status. The higher the income, the less likely it is that users will be affected by mobile health apps in terms of approach (Wald=17.252; B=-0.155), decision making (Wald=9.749; B=-0.120), or consulting (Wald=14.036; B=-0.142). The significant effect of higher income as a pull factor on the effect of mobile health apps indicates that income may increase the likelihood of using less technology for both leisure and health concerns. Being in a spousal relationship increases the likelihood of a changed approach (Wald=37.351; B=0.772) to decision making (Wald=10.562; B=0.417), but it has no significant effect on consulting regarding a health concern (Wald=2.381; B=-0.195). The results indicate that individuals in spousal relationships are more likely to address the health concerns of their spouse as well as their own.

Mobile Health Apps' Use and Situational Effects

To explore the direct impact of technology on (1) lifestyle and (2) health management behaviors, we proceed in a stepwise manner. The stepwise method enables us to explore the extent to which variables in each set of predictors increase or decrease the likelihood of predicting health lifestyle and health management behaviors. First, we introduced variations in mobile health apps' use—the number of mobile health apps and update frequency. Second, we predicted variations in health attitudes following the use of mobile health apps. Third, we introduced socioeconomic variables, controlling for both mobile health apps' use and health attitudes.

In the final step, we introduced *situational* variables to assess the extent to which the use of mobile health apps is beneficial to lifestyle and health management behaviors.

Use of Mobile Health Apps

The findings in Table 4 indicate that the use of mobile health apps (eg, the number of mobile health apps and updating frequency) has a differential effect on health management behaviors. More specifically, using a greater number of mobile health apps significantly decreases the likelihood of lifestyle health management behaviors among users (Wald=21.295;

B=-0.863), but it has no significant effect on health management behaviors (Wald=3.154; B=-0.220). However, regular updates increase both lifestyle (Wald=61.795; B=2.099) and health management (Wald=12.532; B=0.513) behaviors.

Health Attitudes

Next, we examined the effects of health attitudes on health management behaviors. An empowering change of approach (Wald=32.110; B=1.493), making a decision (Wald=9.333; B=0.865), and seeking further consultation (Wald=70.820; B=2.713) regarding a health concern following the use of mobile health apps increase the likelihood of lifestyle health management behaviors. Similar effects are evident regarding health management behaviors, with the exception of change in approach. Making a decision (Wald=34.915; B=0.914) and seeking further consultation (Wald=9.796; B=0.481) regarding a health concern following the use of mobile health apps increase the likelihood of health management behaviors.

Socioeconomic Effects

The most prominent findings indicate the mixed effects of socioeconomic variables in predicting lifestyle and health management behaviors. Older adults (Wald=44.445; B=-0.070) and men (Wald=50.567; B=-1.736) were less likely to instigate lifestyle health management behaviors following the use of mobile health apps. Furthermore, educated users were more likely to pursue lifestyle health management behaviors following the use of mobile health apps (Wald=85.811; B=0.641). The combined effect of the use of mobile health apps and socioeconomic factors clearly indicates that mobile health apps have an empowering effect on both lifestyle and health management behaviors among users. Nonetheless, the extent to which these sets of factors remain effective necessitates considering situational effects that can possibly reverse this general trend.

Situational Effects

Overall, the results pointing to the influence of situational effects on lifestyle and health management behaviors are indicative of the significance of such effects on health management behaviors. Situational effects have mixed effects. They can have a negative effect on lifestyle health management behaviors and less on health management behaviors. A chronic disease (Wald=32.221; B=-1.359), a health emergency (Wald=9.367; B=-1.842), a health crisis (Wald=4.795; B=-0.751), and a health change (Wald=7.583; B=-0.699) all decrease the likelihood of adopting lifestyle health management behaviors. Moreover, the effect of situational factors on health management behaviors is not uniform. Chronic disease (Wald=50.472; B=1.007) and health crises (Wald=27.256; B=1.086) increase the likelihood of health management behaviors. In contrast, a health emergency (Wald=13.101; B=-1.012) and a health change (Wald=16.290; B=-0.679) decrease the likelihood of health management behavior.

These results provide the following conclusions. First, it is evident that situational effects create some kind of general perception of risk [15] because they inhibit the effective impact of mobile health apps on lifestyle behaviors, such as weight loss or physical activity. Second, there is apparently a difference

in the way individuals perceive the *threat* related to their situation. Chronic diseases, but not health crises, often manifest in the form of health management *routine* [77]. In this case, the use of mobile health apps helps to address the health concerns of individuals who are already aware of their health condition. However, in the case of an emergency or a sudden change in health, mobile health apps may become irrelevant and possibly risky [8].

Discussion

Principal Findings

In this study, we assessed the impact of mobile health apps on health attitudes, lifestyle health management behaviors, and health management behaviors. We adopted a cost-benefit approach and applied the push-pull perspective to introduce a set of *situational* factors including health crises, changes in health condition, and sudden hospitalization. We considered the possibility that situational health factors affecting individual affordances may, in some cases, enhance (push) the adoption of lifestyle and health management behaviors following the use of mobile health apps, whereas in others, they may restrain (pull) this adoption. Overall, the classification model indicates that mobile health apps are only partially effective because a set of *situational* effects moderates the link between the use of mobile health apps and health management behaviors. In fact, although a large percentage of individuals change their health-related attitudes following the use of mobile apps, a much smaller portion adopts health management behaviors. These findings support most of the proposed hypotheses.

First, technology use clearly affects health attitudes, increasing the likelihood that mobile health apps will change attitudes and causing users to seek out advice about health concerns based on the knowledge acquired through mobile health apps, but it is also possible that the users may go a little *overboard* and become confused and distressed [76]. Second, although positive attitudes increase the likelihood of developing empowering health attitudes [53], these attitudes may not necessarily prompt users to actually engage in health management behaviors. Indeed, the occurrence of situational effects, such as a sudden change in health, health crises, and hospitalization generate *different realities* that shape individuals' affordances and define the limits of their own cost-benefit framework that accounts for the push and pull factors and encourages or discourages health management behaviors [8]. As a result, for individuals who

experience health-related concerns, tailored programs are less appealing because they have specific needs or even face health risks.

These findings help in assessing similar conclusions in recent studies [6,8,69] and necessitate considering *situational* effects in an individual's health management behavior in both lifestyle and health management behaviors. Therefore, the prediction of health management behaviors following the use of mobile health apps aiming to increase the likelihood of adopting effective health management behaviors should be assessed within a push and pull framework.

Strengths and Limitations

The use of mobile apps for health purposes represents an important breakthrough in ICT. The availability of mobile health apps affects individuals wishing to enhance their levels of HE and improve their health routine. Individuals use these apps for various health purposes. These include lifestyle behaviors, such as quitting smoking, adhering to physical fitness programs, and accessing health services, and health management behaviors, such as adhering to sugar and blood pressure monitoring, cancer and heart disease management, and psychotherapy support. However, existing studies supporting the beneficial effects of mobile health apps have focused mostly on specific health groups and less on a wide range of individuals with or without health concerns. As a result, there is little evidence of a cross-sectional comparison of the usefulness of mobile health apps. This is especially important considering that health institutions and professionals report that they rely increasingly on the use of mobile health apps to increase health awareness and promote adherence to health management practices.

Conclusions

We conclude that the effect of mobile health apps on health management behaviors should intersect with both the objective qualities of those apps and health situational factors and not just induce empowering health attitudes [61]. Designers of mobile health apps should take into account the effect of possible barriers to effective use of apps. Acknowledging these barriers will assist to develop in-depth insights into how and why health lifestyle and health management behaviors develop following the use of mobile health apps. These insights will in turn assist individuals who depend on the effective use of these apps to address frail health conditions and attain effective home care support.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Distribution of central variables (N=1491).

[PDF File (Adobe PDF File), 244 KB - [humanfactors_v8i2e21251_app1.pdf](#)]

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Abbreviations

HBM: health belief model
HE: health empowerment
ICT: internet communication technology
SDH: social diversification hypothesis
TAM: technology acceptance model

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Original Paper

Usability Evaluation of a Tablet-Based Intervention to Prevent Intradialytic Hypotension in Dialysis Patients During In-Clinic Dialysis: Mixed Methods Study

Matthew Willis^{1*}, MA, MPhil, PhD; Leah Brand Hein¹, MA; Zhaoxian Hu², MS; Rajiv Saran³, MS, MD, MBBS; Marissa Argentina⁴, MSW; Jennifer Bragg-Gresham^{3,5}, MS, PhD; Sarah L Krein^{6,7}, RN, PhD; Brenda Gillespie⁸, PhD; Kai Zheng², PhD; Tiffany C Veinot^{1,9*}, MLS, PhD

¹School of Information, University of Michigan, Ann Arbor, MI, United States

²School of Information and Computer Sciences, University of California Irvine, Irvine, CA, United States

³Division of Nephrology, Department of Medicine, University of Michigan, Ann Arbor, MI, United States

⁴National Kidney Foundation, New York City, NY, United States

⁵Kidney Epidemiology and Cost Center, University of Michigan, Ann Arbor, MI, United States

⁶Department of Internal Medicine, University of Michigan, Ann Arbor, MI, United States

⁷Veterans Affairs Center for Clinical Management Research, US Department of Veterans Affairs, Ann Arbor, MI, United States

⁸Department of Biostatistics, Consulting for Statistics, Computing and Analytics Research, University of Michigan, Ann Arbor, MI, United States

⁹School of Public Health, University of Michigan, Ann Arbor, MI, United States

*these authors contributed equally

Corresponding Author:

Matthew Willis, MA, MPhil, PhD

School of Information

University of Michigan

105 South State Street

Ann Arbor, MI, 48109

United States

Phone: 1 7347632285

Email: mandwill@umich.edu

Abstract

Background: Patients on hemodialysis receive dialysis thrice weekly for about 4 hours per session. Intradialytic hypotension (IDH)—low blood pressure during hemodialysis—is a serious but common complication of hemodialysis. Although patients on dialysis already participate in their care, activating patients toward IDH prevention may reduce their risk of IDH. Interactive, technology-based interventions hold promise as a platform for patient activation. However, little is known about the usability challenges that patients undergoing hemodialysis may face when using tablet-based informatics interventions, especially while dialyzing.

Objective: This study aims to test the usability of a patient-facing, tablet-based intervention that includes theory-informed educational modules and motivational interviewing–based mentoring from patient peers via videoconferencing.

Methods: We conducted a cross-sectional, mixed methods usability evaluation of the tablet-based intervention by using think-aloud methods, field notes, and structured observations. These qualitative data were evaluated by trained researchers using a structured data collection instrument to capture objective observational data. We calculated descriptive statistics for the quantitative data and conducted inductive content analysis using the qualitative data.

Results: Findings from 14 patients cluster around general constraints such as the use of one arm, dexterity issues, impaired vision, and lack of experience with touch screen devices. Our task-by-task usability results showed that specific sections with the greatest difficulty for users were logging into the intervention (difficulty score: 2.08), interacting with the quizzes (difficulty score: 1.92), goal setting (difficulty score: 2.28), and entering and exiting videoconference rooms (difficulty score: 2.07) that are used to engage with peers during motivational interviewing sessions.

Conclusions: In this paper, we present implications for designing informatics interventions for patients on dialysis and detail resulting changes to be implemented in the next version of this intervention. We frame these implications first through the context

of the role the patients' physical body plays when interacting with the intervention and then through the digital considerations for software and interface interaction.

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KEYWORDS

user interaction; dialysis; usability; informatics intervention

Introduction

Chronic kidney disease (CKD) is the ninth leading cause of death in the United States [1,2]. The most advanced stage of CKD is end-stage renal disease (ESRD) wherein dialysis or transplantation is required for survival. In 2017, 746,557 Americans had ESRD [3]. However, transplants are not an option for many patients due to their health status and limited organ supply. Hemodialysis is the most common form of therapy for ESRD, with over 500,000 (about 70%) of all dialysis patients treated by hemodialysis rather than alternative dialysis modalities [3]. Hemodialysis is a demanding activity for patients, with a frequency of three times a week and each session lasting approximately 4 hours. The stability of these sessions varies, but an average of 20% of all hemodialysis sessions become unstable, most commonly due to intradialytic hypotension (IDH). Hemodialysis sessions are not always stopped early or interrupted. To improve the blood pressure, the patient is offered an intervention such as a bolus of saline or slowing of the ultrafiltration rate and/or placing the patient in the Trendelenburg position. IDH can result in cramping, dizziness, vomiting, fainting, and fatigue, with highly unstable sessions potentially leading to hospitalization or death [4-6]. Although IDH presents serious risks to patients undergoing hemodialysis, modifying patient behavior may prevent its occurrence. A promising approach to IDH prevention is to activate patients on hemodialysis to become more engaged in IDH prevention behaviors, such as monitoring their fluid intake and sodium consumption and ensuring they are dialyzed for their full prescribed times [7].

There is strong evidence suggesting that the use of digital informatics interventions is an effective way to support hemodialysis patient activation. In extensive reviews, Hibbard and Greene [8] and Sawesi et al [9] show that digital informatics interventions can enhance hemodialysis patient activation, health behaviors, and health outcomes. Hibbard and Greene [8] further conclude that activated patients on hemodialysis have better health outcomes and care experiences. Our previous work has shown that due to the fast pace of hemodialysis care in the United States, nursing staff are not able to perform additional tasks to educate patients in using new technologies or to perform troubleshooting activities [10]. Accordingly, we developed a digital informatics intervention to promote behavior change and activate patients on hemodialysis toward IDH risk reduction. Due to the lack of nursing staff time, we have also developed the intervention to include education of patients on hemodialysis to perform these tasks themselves. However, little prior work has considered how to design usable informatics interventions specifically for this patient population.

Similar work by Harrington et al [11] has investigated the use of a tablet-based application to support real-time monitoring and communication between patients and care providers. Their study looked at peritoneal dialysis at home, not in clinical settings, and was not developed with the aim of reducing a specific risk to which these patients are exposed. They also evaluated perceived satisfaction among the patients with using the application but did not examine interaction challenges. Furthermore, a systematic review of self-management interventions for patients with CKD identified a total of 23 studies that provide support for patients receiving dialysis [12]. These interventions were designed for specific tasks such as recording information (eg, meal logs and dietary intake), communicating with providers to monitor events and adherence to treatments, sending safety alerts for medications that may impair renal function, providing educational information, and monitoring of blood pressure and body weight. Another systematic review investigated different intervention types and evaluation models using mobile health technologies for the management of patients undergoing dialysis [13]. The systematic review found most functions of interventions to involve food tracking and self-monitoring. It also identified most outcome measures to be related to patient satisfaction or clinical effectiveness and did not evaluate interaction. Of the evidence provided by the two abovementioned systematic reviews [12,13], none of the studies reviewed had investigated the use of an eHealth intervention to improve hemodialysis patient outcomes for IDH or other challenges faced by these patients that can be addressed by self-management.

To develop informatics interventions for patients undergoing hemodialysis so that their risk of IDH is lowered, it is critical that they find the technology easy to use and that it provides a high-quality experience to them. We use the term "usability" to frame our investigation around the construct of interventions being easy to use, easy to learn, and easy to remember. Gould and Lewis [14] recommend three design principles when designing for usability. The first principle is that the system should have an early focus on the intended users and the tasks that they will need to accomplish by using the system. Accordingly, during early stages of development, we included users in the design process of this intervention [10,15-17]. Now that the first iteration of the previously developed intervention is available for patients on hemodialysis to interact with, this study aims to put into practice Gould and Lewis' final two design principles: empirical measurement using qualitative or quantitative measures and iterative design process—learning from users and implementing that feedback into the next iteration of the design. In this study, we are particularly interested in the usability characteristics of effectiveness (are patients able to do learn what they need from the intervention?) and efficiency (can the patients easily learn and use the

intervention on their own?). With this operationalization of usability, we aim to investigate how patients undergoing hemodialysis interact with the intervention and establish how to make the intervention usable for them when they run into difficulties [18].

Therefore, we pose the following research question to frame this study: What interaction challenges occur when patients undergoing hemodialysis use a tablet-based intervention in the dialysis clinic setting?

Methods

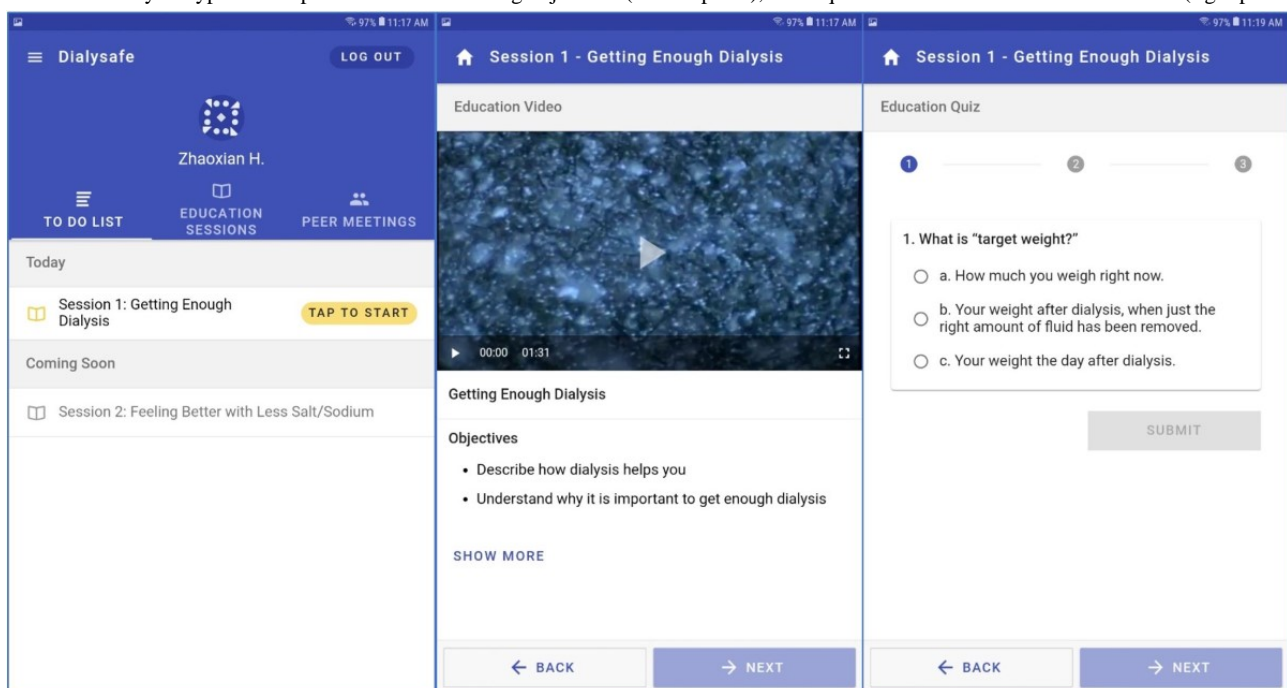
Description of the Intervention

Our previous work discusses the use of peer mentoring for young adults on hemodialysis [16,19], essential information design considerations of the hemodialysis clinical environment [20,21], information preferences of patients receiving dialysis [22], workflows used by clinicians to help prevent IDH [10], development of a patient-centered definition of unstable dialysis sessions [15], and results of a user-centered design process for developing the intervention evaluated in this study [17]. Based on this prior work, we have deployed a tablet-based intervention

that was developed using the Ionic Framework's app development platform along with AngularJS for the Android operating system, designed to run on a Samsung Galaxy tablet. The video player in the applications used the HTML5 video player Videogular2 for Angular.

The intervention software (see screenshots in Figure 1) that patients interact with is organized into five sections, with each section covering one topic of IDH, that aim to activate patients on hemodialysis toward IDH prevention: (1) getting enough dialysis (which refers to completion of the amount of dialysis prescribed), (2) feeling better with less salt or sodium, (3) limiting fluid intake, (4) feeling better on dialysis and having easier sessions, and (5) getting more involved in one's care. Each section includes educational content delivered via screencast, quizzes, story videos from other patients on hemodialysis, goal-setting modules, action plans, and motivational interviewing-based peer mentoring sessions delivered via tablet videoconferencing. All elements are to be delivered while the patients dialyze by using clinic-provided tablets, earphones, and Wi-Fi service. Clinic staff will provide tablets, disinfect them after each use, and place them in a charging cabinet.

Figure 1. Screenshots from the tablet-based intervention: homepage showing the main to-do list (left panel), a typical educational model presenting content on intradialytic hypotension prevention with learning objectives (middle panel), and a quiz that is delivered after each session (right panel).



After the patients undergoing hemodialysis log into the application by using their chosen username and password, the intervention presents a to-do list aligned with the current session theme. There are three tabs: The “To Do List” (Figure 1, left panel) acts as a homepage wherein the user can view all activities with which they can engage. Past educational content can be reviewed by navigating to the “Education Sessions” tab. Times and dates of future peer mentor sessions can be reviewed by navigating to “Peer Meetings.” Patients may view the themes of the upcoming sessions (see “Coming Soon”) on the homepage but may not be able to enter them until all prerequisite sessions are complete. It is important to note that peer mentor-mentee

matching is managed by the National Kidney Foundation (NKF). Mentees undergo an intake procedure with the NKF staff to understand the patient's characteristics, interests, illness experiences, and challenges. The NKF then uses this information to match compatible mentors to the mentee.

All five educational sessions begin with an educational video (Figure 1, middle panel). This is the main informative part of the session, featuring slides developed in collaboration with the NKF; a screencast video prerecorded by an NKF staff member that shows the slides and has a voiceover. Each video focuses on what patients on hemodialysis can do to lower their risk of

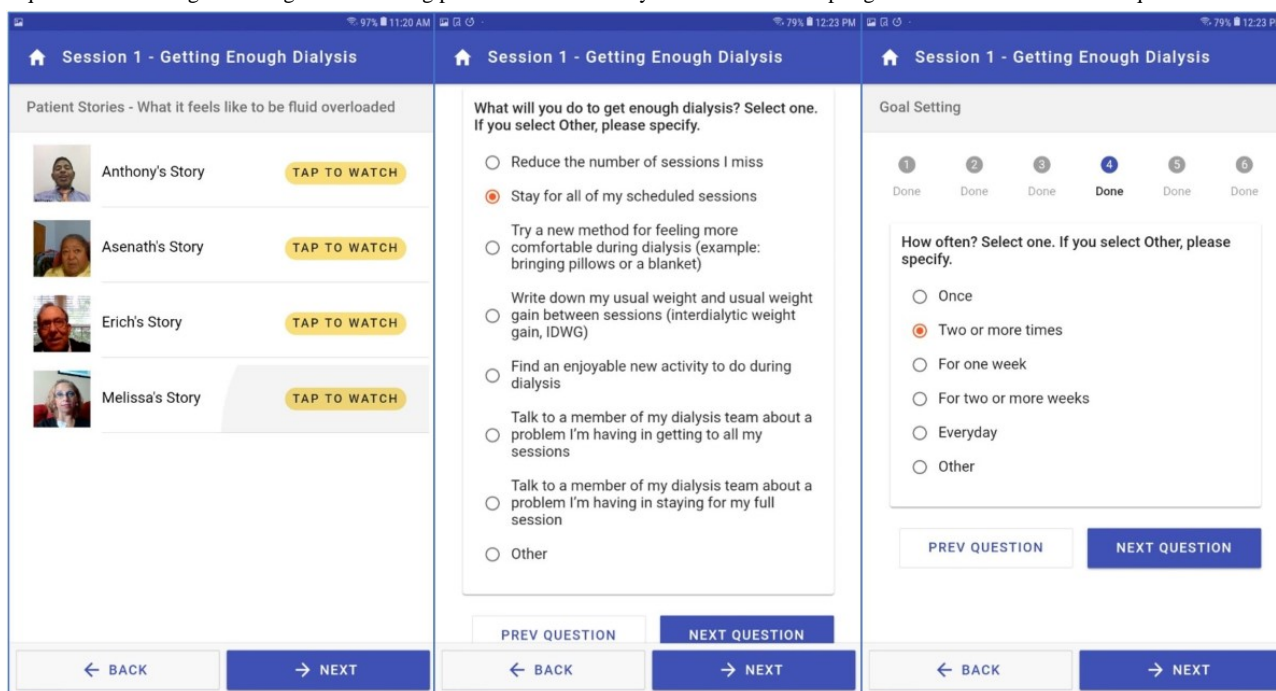
IDH and the rationales for these actions. Session learning objectives, which are discussed in the first few minutes of each video, are listed below the embedded video player. To ensure that the patients receive the material, the video can only be skipped or fast-forwarded after the patient has viewed it once in full.

After viewing the video, patients are asked to test their knowledge on the content by answering a short quiz comprising two to four questions (Figure 1, right panel). All questions are

multiple-choice questions, and answers refer to the session content.

The intervention includes a video library of hemodialysis patient stories (Figure 2, left panel). Each session includes two to four patient story videos in which real patients receiving dialysis share their answers to a question related to that session's theme. All patients in the videos were recruited by the NKF. Patients who use the intervention may view as many patient story videos as they wish.

Figure 2. Screenshots from the tablet-based intervention showing a video library of hemodialysis patient stories (left), the quiz for module 1 (middle), and a question from the goal-setting module asking patients how often they will commit to adopting a certain behavior from the quiz.



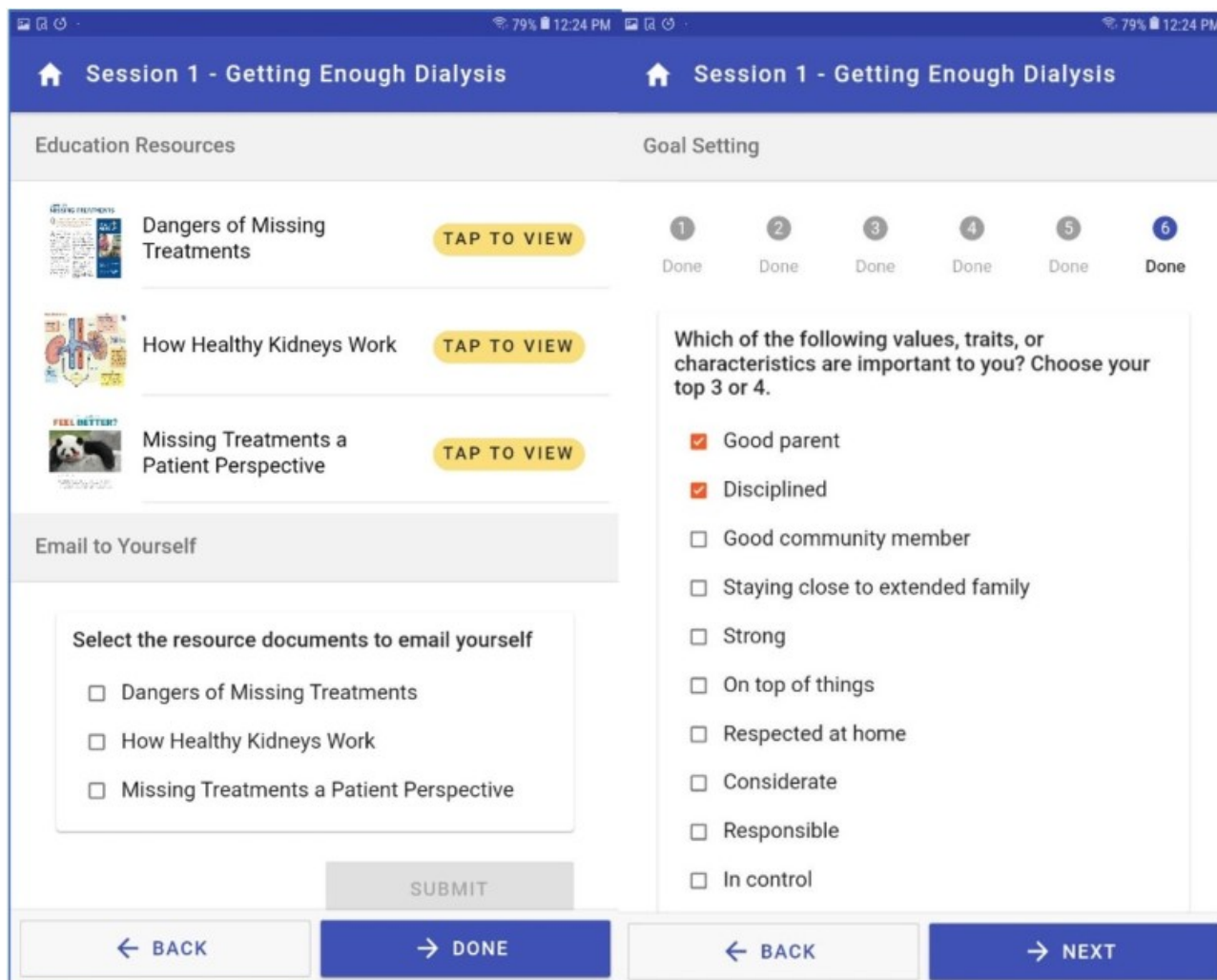
In the goal-setting module (Figure 2, middle and right panels), patients are prompted to select a goal that will help them improve their health behavior in relation to the theme. A set of prepopulated goals are provided, with content drawn from hemodialysis patient and care partner focus groups. Next, the patients select how often, how much, and when they will start the behavior (Figure 2, right panel). The options available on the goal-setting screen informs the motivational interviewing-based discussion between patients on hemodialysis and their peer mentors. This discussion is mediated by the application through a videoconferencing software that can also be accessed via the tablet. The answers provided by the patients on this screen are accessible to peer mentors through a peer mentor-facing web portal.

The intervention also provides the ability for patients on hemodialysis to obtain information when at the clinic or at home (Figure 3, left panel). Patients using the intervention can open and explore all documents listed within a session. They have

the option of retaining the materials as “digital handouts” by sending a copy to themselves via email. This creates a simple process of collecting resources for review outside of dialysis hours.

In the first session, there is also a values selection exercise in which patients can choose from a list or write their own list of values, traits, or characteristics most important to them (Figure 3, right panel). Examples of values mentioned in the intervention are “being a good parent,” “being a good spouse or partner,” “being competent,” or “feeling energetic.” This element of the intervention is informed by prior work that shows linking values to health goals is a powerful tool to support behavior change [23]. This effectively motivated the patients’ health behavior goals with their “why” for making a change (ie, *why* they choose to take action to prevent IDH)—because of the values that they select in the exercise. These values are viewable by the peer mentor and form the basis of discussion with patients about their own personal reasons for effecting a change.

Figure 3. Screenshots from the tablet-based intervention: supplemental materials related to each learning module that patients can email themselves to review outside of dialysis hours (left panel); goal-setting module wherein patients select values, traits, or characteristics most important to them (right panel).



Recruitment

Prior work on sample size for usability studies has shown that, for the size and complexity of our mobile app, a total of 15 users is acceptable to discover virtually all software problems [24-26]. We recruited 14 patients over a 2-day period at a University Hospital hemodialysis clinic in a Midwestern State, which has about 83 patients. The facility models team-based care where teams are composed of nurses, patient care technicians, a dietitian, social worker, physicians, and advanced practice providers. Patients receiving hemodialysis that were awake while dialyzing were approached by the clinical staff. Clinicians informed these patients about the study and asked if they were interested in participation. Two research staff members then approached interested patients to obtain informed consent. To ensure that the intervention was appropriately designed for its most likely users, patients were intentionally selected to be representative of the demographics of patients on hemodialysis in terms of race, age, and gender [27]. All interviews and observations were conducted in the dialysis clinic setting. The usability testing was cross-sectional, and participants only had access to the intervention during the user testing. The study was declared exempt from oversight by the Institutional Review Board (HUM00159531) at the University of Michigan.

Data Collection

Data were collected using two methods to leverage the (1) the think-aloud method [28,29] and (2) structured researcher observation of patients on hemodialysis using the intervention. We used a think-aloud-based interview guide containing the questions for tasks to be completed on each screen of the application; this method permitted the collection of participants' subjective perceptions of usability challenges. We also used a data collection instrument to capture objective observational data regarding what interaction tasks the patients had attempted and a score for how difficult each task was for them. Two field researchers were trained to take notes and assign scores. All data gathered were based on objective criteria for which available data were highly visible. These criteria include participants' difficulty with performing each task: (1) on their own with little difficulty, (2) with some difficulty, or (3) with considerable difficulty and requiring assistance to complete the task. We applied these scores for tasks such as logging into to the application, reviewing the "to-do" list, playing and stopping a video, taking a quiz, and entering and exiting a video conference meeting with a peer mentor. As patients worked their way through the tasks, they were asked to verbalize their thoughts, explaining how they interpreted the screens, what

they thought they would experience at each stage, or what questions or problems they had. While patients were describing their thoughts, a researcher took field notes, including direct quotes. Each observation session lasted from 20 minutes to 1 hour. The evaluation session began when field researchers sat with a patient to have them navigate through the application to perform each task.

Data Analysis

We entered the numerical scores (on the scale of 1 to 3) for each task level of difficulty into a spreadsheet and calculated mean scores for each interface task in a Microsoft Excel spreadsheet. We also created a case-by-case display to capture field notes

[30,31] alongside each patient's interaction difficulty score to evaluate reasons for the difficulty scores. Finally, we performed qualitative content analysis to inductively categorize field notes and organize them into themes concerning challenges experienced by patients on hemodialysis in using the intervention software.

Results

Participant Demographics

Table 1 below shows the gender, race, age range, and previous touch screen experience of the study participants.

Table 1. Study demographics of patients undergoing hemodialysis (N=14) and their experience in using touch screen devices.

| Characteristic | Participants |
|--|--------------|
| Gender, n (%) | |
| Male | 7 (50) |
| Female | 7 (50) |
| Race, n (%) | |
| White | 5 (35.7) |
| African American | 9 (64.3) |
| Age range (years), median (IQR) | |
| 41-74 | 58 (12.5) |
| Touch screen experience, n (%) | |
| Yes | 9 (54.3) |
| No | 5 (35.7) |

General Constraints

Observations showed that patients undergoing hemodialysis have *limited mobility and reach* depending on where their access port for dialysis needles is located on their arm or chest. Because chest access confers an elevated risk of serious infections, many patients have access in their arms. With an arm access, patients have large needles inserted into their arm, appended with soft tubes through which blood is removed and then returned. This connection to the machine is sensitive to movement, typically leading to limited mobility in their arm. Consequently, as one patient noted, "In dialysis, I only have one hand to use." This limits how patients can hold and tap the tablet. If they used a thumb to tap the screen because of these issues, the device often failed to register their tap. Patients are further constrained during blood pressure checks—as exclaimed by one patient during usability tests, "The machine's got me tied up now." In such situations, patients required help to navigate the tablet. The inability of the patient to operate the tablet also influenced the usability data we were able to collect. At times, when the field researcher would ask a participant to select a specific menu item or play a video, the participant could not physically perform the task at that moment. This led to difficulty in using the intervention because it left the patient in a position where they could not be able to do what they wanted to do, when they wanted to do it.

Our observations also revealed that *dexterity issues* are common in patients undergoing hemodialysis. For instance, those who experienced limited dexterity or tremors while dialyzing faced a challenge in being able to accurately tap in the intended area. This created a feedback deficiency—patients did not know when they had activated the button after having tapped on it several times. Aware of this difficulty, one patient suggested, "You may want to add clicks or noises when typing," to help patients know when they touched the right spot. This was not an issue of learning; they did not need to know how to use the device but rather wanted to know if their input was accepted by the device, if they pressed it correctly, or if they touched the screen in the right manner in the right location.

Impaired vision and use of reading glasses are also common in patients on hemodialysis, due in part to diabetes and hypertension being the most common causes of kidney failure. Accordingly, the intervention was designed to accommodate a general need for large print and buttons, as well high-contrast text and images. Despite designer efforts, there were legibility issues with reading a smaller font on one of the screens; during the think-aloud sessions with the quiz feature, several patients stated, "I can't read it," while taking the quiz.

Furthermore, we noted a difference between participants' perceptions based on their previous experiences with touch interfaces. About two-thirds of our sample (9/14, 64%) had prior experience with touch screens, whereas the remaining

one-third did not have any touch screen experience. Patients without touch screen experience were confused when the screen timed out when they were not interacting with the tablet, and they did not intuitively know how to tap elements on the screen, sometimes holding taps for too long or too short a time or too lightly. In some cases, the patients did not have prior knowledge of interaction through tapping the screen, or of what elements would not respond to a tap. The clearest example of this was patients not knowing how to interact with the slider on the quiz screen, as described below.

Task-by-Task Usability Results

The usability evaluation revealed several aspects of the intervention application with which patients had difficulty interacting. Some of these difficulties were not limited to the intervention application but extended to the accessibility of, and configuration options for, the Android mobile operating system and video player running underneath the intervention application. As described below, many of the interaction challenges observed concerned visibility and readability of text and problems with gestures or taps.

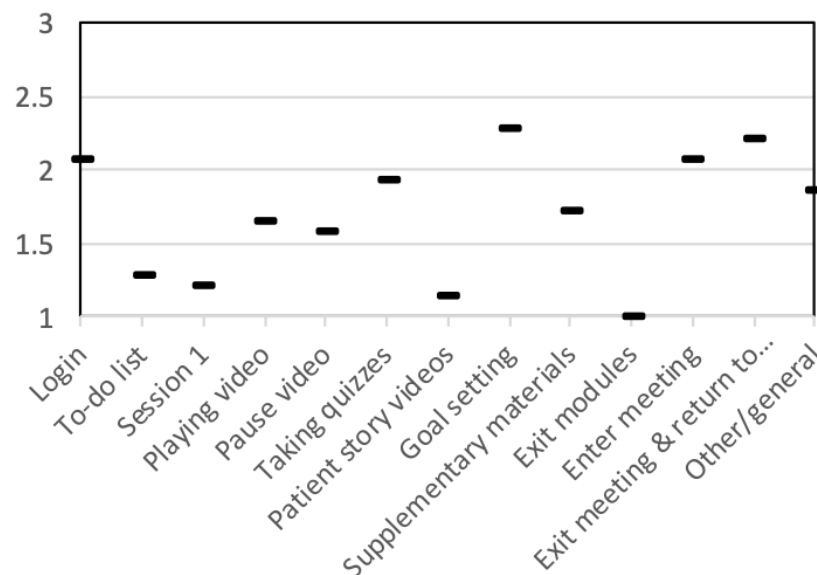
Figure 4 shows the average usability scores for each assigned task based on ratings—using a scale of 1 to 3—of how difficult the tasks were for patients. The easiest interactions were watching videos and exiting learning modules. The most challenging tasks, which often required help to complete, were goal setting, exiting live video chats, and returning to the intervention application from the video chat application. We

also identified several usability issues that were pervasive throughout interactions with the intervention but became more pronounced when using certain screens. These pervasive issues included tapping, reading text, selecting text entry fields, and registering interactions when touching the screen. Each of these issues are explored further below.

The login screen had an average score of 2.07. What patients found challenging here was selecting the appropriate text entry field; furthermore, half of the patients had problems with the keyboard layout. Specifically, they struggled to find the back key, had trouble reading or interpreting legends on the keyboard, confused a zero (0) with the letter “O,” had problems with case sensitivity and accidentally engaging caps lock, or were unfamiliar with typing an email address on a touchscreen keyboard and voice input functionality displayed on the keyboard. The keyboard was available as is in the Android operating system and was not specifically designed for patients on hemodialysis or for the study intervention.

Once logged in, the patients were greeted with the to-do list. Although this screen was unique to the intervention, it was easy for them to navigate, interact with, and understand; the mean difficulty score was only 1.28 (SD 0.73). Some reports concerned needing larger print for certain items, additional formatting—such as bold typeface and larger font—to help with clarity of understanding list items, and minor visual design enhancements that would help the patients understand the purpose of the to-do list.

Figure 4. Difficulty of use scores (scale of 1 to 3) for each intervention application feature. A score of 1 indicates the participant was able to accomplish the task on their own with little difficulty. A score of 2 indicates some difficulty and a score of 3 indicates considerable difficulty requiring assistance to complete the task. The y-axis represents the difficulty score, and the x-axis shows the task performed by the patients.



Patients tested the first session of the intervention. They had little difficulty with this activity (difficulty score: 1.21). However, playing videos for the first learning session posed slightly more difficulty as this section received a score of 1.64 and saw multiple patients struggling with controlling the audio volume level and the screen timing out. We also asked the participating patients to pause the video (difficulty score: 1.57);

several patients did not know how to do this and needed a prompt, as well as instructions as to how to exit the video when it was set to full screen.

The intervention quizzes required patients to make dexterous tap gestures to select and submit responses to multiple-choice questions. This proved to be a difficult task (difficulty score: 1.92) for the patients on hemodialysis due to the use of only

one hand, and even more so for those who had tremors, unsteady hands, or lotion or other fluid applied on their hands. This complicated the ability of a capacitive touch screen to register touch gestures; one patient summarized this experience in the following colorful manner: “This thing is a pain in the ass [sic]” (stated twice), and then, “This thing is really...you have to tap it light.” It is important to note that this was the first screen in the intervention that challenged some patients’ understanding of interactivity, as some patients would tap too long or too quickly or tried to double tap certain parts of the screen to select answers. This screen also presented a challenge in interpretation, with one patient reporting, “I don’t get this, where to put my answer,” and then, “I’m not sure where to get the answer” about how to interact with the quiz.

Patients were asked to view patient stories, pause the video, exit the full-screen video, and navigate back to the video to continue watching. Patients faced little resistance in performing these tasks; this had an average difficulty score of 1.14. While reviewing this material, some patients also gave feedback that they enjoyed the videos and saw them as beneficial; for example, one participant said, “It’s some interesting stuff on here if you are new to dialysis...If you are new and it’s your first time on dialysis, this is good.”

For all but 3 participants (11/14, 78%), goal setting proved to be the most challenging and difficult intervention screen for patient interaction (difficulty score: 2.28), requiring guidance to complete all interaction tasks. Specifically, the slider for some of the quiz questions proved to be difficult to interact with; for instance, one patient said, “That’s a tricky button.” Additionally, there were also *Next* and *Previous* question buttons just above the *Back* and *Next* buttons for the main application. This was a frequent point of confusion for patients; one said it was “A little confusing, time consuming.” Another patient asked, “Is this different NEXT?...the extra step probably would get tedious for some people.” Lastly, this task showcased some of the touch interface problems that were symptomatic of observed challenges in the use of a touch screen device. One patient commented, “It looked like it went somewhere, but it didn’t” (referring to multiple touches to get the screen to register). Another voiced a problem with predicting how the screen would react to touch: “[I] shouldn’t touch anything before I finish reading.”

As stated, the intervention allows patients to email a PDF file of supplementary materials to their personal email address. Patients found a specific issue with the placement of the *Next* button on the screen such that if they double tapped the screen, they could miss the prompt to email the document to themselves. Patients required relatively little prompting (difficulty score: 1.71) for this screen. After these tasks, the patients were directed to exit the learning module, a step that was completed with no challenges or need for support; it was the only task that with a difficulty score rating of 1.0.

When using this intervention, patients will need to interact with a video conferencing application to connect with peer mentors; thus, the application is programmed to automatically launch a meeting in the videoconferencing platform BlueJeans [32]. Patients had moderate difficulty (difficulty score: 2.07) with

this task. Most observed challenges concerned how to join video meetings, and there were interface issues in the external video conferencing software. For example, to join a meeting room in the video software, patients needed to press a white *Join* button; however, almost half of the patients (6/14, 43%) thought it was a notification or text, and not a button. Accordingly, they were not aware that they needed to press it. Other parts of the video interface also became confusing, with one patient saying aloud, “I’m looking at controls at bottom, because it is red, not sure if I should hit it.” Patients had similar, moderate challenges of navigating the interface to exit the video chat room and returning to the main intervention application (difficulty score: 2.21).

Discussion

Principal Findings

The intervention was developed from in-clinic observations, interviews, and patient focus groups that included participatory design activities. Issues related to impaired vision and dexterity were raised in this early work and were taken into account during the design of the intervention. Nevertheless, we found that despite our efforts in this area, the intervention needed further refinement to address these issues.

Mobility challenges unique to patients undergoing dialysis concern restrictions to movement owing to the use of devices such as blood pressure machines, dialysis machines, associated wires and tubes, as well as tight clinical spaces or dialysis chairs [21]. These patients need the ability to comfortably hold and manipulate a tablet while sitting on the dialysis chair so that they can use it during hemodialysis. For the intervention to be successful and provide a high-quality experience, patients should not have to wait to engage with the intervention until they can fully operate the tablet with both hands (due to blood pressure check-ups or other examinations). Physical limitations need to be accommodated through an interface that can move, adapt, and be responsive. Technologies such as eye tracking could be used, along with thumb-based interaction, to better support body orientation and gaze of patients on hemodialysis with mobility issues.

Another movement-related challenge for these patients was dexterity; this included the use of hands and fingers to hold the tablet and interact with the interface. Aging-related differences are observed, ranging from decrease in grip strength and pinch strength to deterioration of nerve receptors [33]. Typical dexterity issues in aging hands can be exacerbated by vascular and cardiac problems commonly observed in patients on hemodialysis. This creates problems for touch interface-based interactions. Problems include not receiving feedback on interface elements such as buttons, keyboards, scroll bars, and text entry fields. It is difficult for patients receiving dialysis to navigate the interface of the intervention and receive no acknowledgement of what interface element is interactive or whether the system has registered their input. Audio feedback either through spoken word or tones would provide better support for patients, which can be coupled with haptic feedback to provide additional physical response and visual cues that indicate interface input. However, visual cues need further consideration as detailed below.

Like touch, vision changes with age, requiring designers to attend to the specific needs of users to deliver a more equitable interaction experience [34]. Vision challenges in our patient sample include easily identifying text, controls, buttons, icons, and other parts of the interface. As previously mentioned, although visual cues can be utilized to convey interface interaction, it is important that these be consistent and standardized. To accomplish this, there is a need to leverage design patterns for presenting and perceiving information such as differentiating between interface elements and visual notifications [35].

Without addressing these concerns related to the physical body and accessibility of patients on hemodialysis, informatics interventions risk introducing unwanted challenges to the participants, potentially resulting in disengagement with, and abandonment of, the intervention—a particularly common result in digital informatics interventions with marginalized groups [36]. Indeed, health status and age are correlated with less use of health technologies [37]. We argue that design should be used to advocate for patients receiving hemodialysis that are often marginalized with respect to how they can use technology and how technology meets their needs to challenge existing disparities in health technology uptake, usage, and benefits. Thus, we stress that patients receiving hemodialysis have a right to amelioration of such interaction problems to create equal opportunities to benefit from health technologies [38].

Limitations

Our study has several limitations. One potential limitation is that we did not use a validated usability instrument such as the Health Information Technology Usability Evaluation Scale (Health-ITUES) or System Usability Scale. However, this was not done because the primary goals of the study were to identify what usability challenges patients on hemodialysis face and how they can be addressed. Another limitation of the intervention may be that the difficulty scores reported in our study were rated by the field researcher and not the participant. We chose this method to obtain objective data and because the field researcher was familiar with the software and trained in using the scale we derived, thus allowing for more accurate measurement of whether tasks were completed. However, these observations were complemented by use of the think-aloud protocol, through which a research team member recorded participants' verbal accounts of their thoughts while they completed the assigned tasks, thus leading to rich accounts of the types of difficulties that they faced. Nevertheless, future usability evaluations might leave an opportunity for developing a self-report scale for patients undergoing hemodialysis to quantitatively rate their perceived difficulty in completing tasks using the intervention. A further limitation is that, due to the presence of researchers associated with the intervention, participants may have been less critical of the intervention than they might otherwise been. However, we note that the study revealed several usability issues in need of correction. Another limitation of this study is that patients were not selected based on whether they have a shunt or fistula providing dialysis access

and how different forms of dialysis access might influence mobility of their dominant hand when using the intervention.

Finally, based on our findings, we developed a list of changes to be implemented in the next version of the intervention; some of these are described below. We increased the font size where needed to make the pages more readable, adjusted the button and button row margin to make it easier to tap, and increased the font size in the alert dialog box. On the goal-setting form, we ascribe both "save" and "next" functions to a singular "save button => next button". The objective with these changes was to reduce the number of required clicks, as we observed that extensive tapping was a problem for patients receiving hemodialysis, particularly those using one hand or their thumbs. Furthermore, on the goal-setting form, we changed the slider bar to the toggle button group. Observations of patient interaction revealed difficulty using one of the sliders to select an option rather than tapping; thus, we changed it to a group of buttons, and each button represented a value in the range. On both the goal-setting form and the quiz screen, we removed the footer section ("Back" and "Next" buttons) and changed the "Next" button for the last question function such that it transitions to the next section. This streamlined interaction for patients on hemodialysis and further reduced the number of taps they needed to make. We also changed values to columns rather than a long page; this reduced the need for scrolling, which was important, because the need for scrolling indicated missed content, as some patients were not aware that they needed to scroll down the page. We also designed a patient training module on both the use of touch screen devices and the intervention itself.

Conclusions

This study evaluated the usability of a digital intervention to engage patients on dialysis that is intended to reduce the patient's risk of IDH when dialyzing. A task-by-task analysis of each screen of the intervention identified usability challenges related to setting goals with a high difficulty score of 2.28, and interacting with the videoconferencing platform, which had a high difficulty score of 2.07 to join a meeting and a score of 2.21 to leave the videoconferencing session and return to the main intervention application. Furthermore, our analysis revealed four general constraints when designing for dialysis patients: dexterity in touch and interface navigation, limitations in movement and device positioning when dialyzing, readability and vision challenges for older patients due to small-sized text, and a disparity between patients on hemodialysis who had no experience with tablets and those who had literacy and knowledge of mobile tablet use. These constraints and challenges in user interaction can prevent or defer effective use of the intervention. When developing informatics interventions for patients on hemodialysis, it is critical that such usability challenges are prevented and that the technology's affordances are leveraged to do so. Future design of informatics interventions for patients receiving hemodialysis should proactively account for these usability issues so that they may achieve their intended effects.

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Authors' Contributions

MW and TCV wrote the manuscript. All authors reviewed the final manuscript.

Conflicts of Interest

None declared.

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Abbreviations

CKD: chronic kidney disease

ESRD: end-stage renal disease

Health-ITUES: Health Information Technology Usability Evaluation Scale

IDH: intradialytic hypotension

NKF: National Kidney Foundation

PCORI: Patient-Centered Outcomes Research Institute

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Original Paper

Development and Implementation of a Multidisciplinary Electronic Discharge Readiness Tool: User-Centered Design Approach

Angela Keniston¹, MSPH; Lauren McBeth¹, BA; Jonathan Pell Sr¹, MD; Kasey Bowden¹, MSN, FNP, AG-ACNP; Stephen Ball², BSc; Kristin Stoeber², BSN; Elaina Scherzberg², BHA, RT(R); Susan L Moore³, PhD, MSPH; Jamie Nordhagen², MS, RN; Amanda Anthony², DNP, CCNS, ACNS-BC; Marisha Burden¹, MD

¹Division of Hospital Medicine, Anschutz Medical Campus, University of Colorado, Aurora, CO, United States

²UCHealth, Denver, CO, United States

³Colorado School of Public Health, University of Colorado, Aurora, CO, United States

Corresponding Author:

Angela Keniston, MSPH
Division of Hospital Medicine
Anschutz Medical Campus
University of Colorado
12401 E. 17th Avenue
Mail Stop F782
Aurora, CO, 80045
United States
Phone: 1 720 240 1431
Email: Angela.Keniston@cuanschutz.edu

Abstract

Background: Typical solutions for improving discharge planning often rely on one-way communication mechanisms, static data entry into the electronic health record (EHR), or in-person meetings. Lack of timely and effective communication can adversely affect patients and their care teams.

Objective: Applying robust user-centered design strategies, we aimed to design an innovative EHR-based discharge readiness communication tool (the Discharge Today tool) to enable care teams to communicate any barriers to discharge, the status of patient discharge readiness, and patient discharge needs in real time across hospital settings.

Methods: We employed multiple user-centered design strategies, including exploration of the current state for documenting discharge readiness and directing discharge planning, iterative low-fidelity prototypes, multidisciplinary stakeholder meetings, a brainwriting premortem exercise, and preproduction user testing. We iteratively collected feedback from users via meetings and surveys.

Results: We conducted 28 meetings with 20 different stakeholder groups. From these stakeholder meetings, we developed 14 low-fidelity prototypes prior to deploying the Discharge Today tool for our pilot study. During the pilot study, stakeholders requested 46 modifications, of which 25 (54%) were successfully executed. We found that most providers who responded to the survey reported that the tool either saved time or did not change the amount of time required to complete their discharge workflow (21/24, 88%). Responses to open-ended questions offered both positive feedback and opportunities for improvement in the domains of efficiency, integration into workflow, avoidance of redundancies, expedited communication, and patient-centeredness.

Conclusions: Survey data suggest that this electronic discharge readiness tool has been successfully adopted by providers and clinical staff. Frequent stakeholder engagement and iterative user-centered design were critical to the successful implementation of this tool.

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KEYWORDS

user-centered design; stakeholder engagement; health information technology; implementation science; interdisciplinary; teamwork; discharge planning; discharge readiness tool

Introduction

Communication across care teams in hospitals is often disjointed, which can lead to delays in care and adverse outcomes and can negatively affect team dynamics [1-4]. Planning for care progression and discharge relies on complex communication across multiple care teams, which are often physically separated from each other [1,5,6]. Discharging patients efficiently and safely continues to challenge health care systems worldwide [7-9]. Delays in discharge have been found to be associated with adverse patient outcomes, including mortality, medical complications such as infections, and impaired mobility or activities of daily living, as well as with slowed patient flow from the emergency department and throughout the hospital; these delays are also associated with increased hospital capacity challenges [7,10-14].

Typical approaches for moving discharge to earlier in the day and improving the flow of hospitalized patients rely on one-way communication mechanisms, static documentation in the electronic health record (EHR), and in-person care team huddles or telephone calls, which often take place on the day a patient is expected to be discharged [2,15-22]. Multidisciplinary rounds are a common workflow in many hospitals during which discharging patients are discussed. However, multidisciplinary rounds often vary in execution across clinical units; some approaches are more or less effective than others, with variable start times, different clinical staff in attendance, different processes for discussing the discharge of patients, and variable perception of effectiveness [23-25]. Many of these solutions rely on processes taking place outside of the EHR and interrupt patient care [26,27].

Effective use of health information technology (HIT) may introduce a degree of standardization to multidisciplinary rounds and huddles, improve discharge communication workflows, and alleviate delays in discharge [28]. Although communication between providers using the EHR is not well studied, data indicate that well-executed communication and collaboration between providers is associated with better patient outcomes, and the application of HIT in specific domains is associated with improved health care quality and safety [29,30].

Tools that enable dissemination of information at both the patient level and team level may provide the greatest utility, as providers and other clinical staff would be able to access information for each individual patient as well as for groups of patients being cared for by a specific team or on a specific floor. Given the success found in the application of HIT in specific domains, such as provider order entry or prescribing of medications [29-32], there is potential for the application of real-time electronic provider-to-provider or provider-to-service communication around the activity of discharge planning.

Addressing the need for a seamless solution to coordinating discharge processes, we developed an innovative tool (the Discharge Today tool) within Epic, the EHR in use at the University of Colorado Hospital, to facilitate communication in real time between hospitalists and other clinical staff regarding discharge readiness and barriers to discharge [2]. We hypothesized that systematic application of stakeholder

engagement and workflow analyses as a part of a user-centered design process would lead to a well-designed HIT innovation that would be readily adopted and consistently used by providers and other clinical staff.

Methods

To guide the design of this tool, we applied several frameworks, including the analytic-deliberative model of stakeholder engagement [33] to enhance our stakeholder engagement efforts, the Coiera communication paradigm [34] to incorporate communication theory, and the Chokshi and Mann process model for user-centered digital development [35] to direct the iterative development of the tool.

Applying the analytic-deliberative model of stakeholder engagement [33], we involved our stakeholder partners, including patients, families and caregivers, clinical staff, clinical leadership, and administrative leadership. The analytic-deliberative model links analysis using information collected and deliberation by stakeholders with the intent of reconciling different viewpoints and making recommendations.

To that end, we met with clinical and administrative staff to gain an understanding of their experiences with the discharge process as well as the communication methods and tools currently used to disseminate information on barriers to discharge and readiness for discharge. We conducted workflow analyses with clinical staff directly involved in discharge communication and care of hospitalized patients. Finally, we engaged with patients who experienced discharge from the hospital through one-on-one discussions with patients and their families or caregivers. Stakeholder engagement to inform user-centered design was imperative to ensure that our Discharge Today tool was successfully integrated into existing workflows such that all clinical staff would use this tool with every patient. However, stakeholder engagement was only one aspect of our systematic approach to user-centered design in a clinical setting.

Similar to other types of computer-supported cooperative work technologies that support asynchronous collaboration, such as email, collaborative creation of documents, technologies designed to capture recommendations, repositories for shared information, and particularly workflow applications, the Discharge Today tool is an asynchronous communication tool [36]. To improve the flexibility, agility, efficiency, and accuracy of communication around discharge, we applied the Coiera communication paradigm [34]. This model describes four stages for communication (task identification, connection, communication, and disconnection) in which errors may occur at any point during the sequence, including how the communication system functions or is used or in the information available to those involved. By supporting asynchronous collaboration, building feedback loop capabilities, and implementing user role-dependent functionality, the Discharge Today tool reduces inefficiencies and, potentially, errors in the delivery of health care during the discharge process.

Using the Chokshi and Mann process model for user-centered digital development [35], we applied the four phases described with a continuous feedback loop between Discover, Define,

Develop, and Deliver. Phase one requires understanding the concepts and processes associated with the work being done, and phase two involves engaging with users to understand how they would use a tool and observing users in a laboratory environment before going live using two specific methods: “think-aloud” and “near-live” [35]. Phases three and four involve iterative development, testing, and optimization of a tool in the setting where the work is actively being done.

Using the methods described in this model, we were able to identify any fundamental incompatibilities between the EHR and typical clinical workflows, which are potential points of failure for provider-facing innovations. In addition, this model helped guard against overdesign of the tool to accommodate workflows, which can actually inhibit adoption.

As a part of our stakeholder engagement process, we applied a novel strategy, brainwriting premortem [37], to specifically engage stakeholders in identifying potential barriers that we might encounter when implementing the discharge readiness functionality in the EHR. The brainwriting premortem exercise was designed by researchers to rapidly stimulate ideas of ways in which an intervention or tool could fail in a focus group setting. This exercise has been found to be an efficient method for engaging stakeholders and generating feedback, specifically because it is designed to imbue a sense of psychological safety among participants [37]. During this exercise, participants were asked to write down all the reasons each of them could think of that would cause this tool to fail. This process was repeated iteratively, with stakeholders adding ideas to existing pages until no new ideas emerged. Upon completion of the exercise, the pages were collected and the content was collated later for consideration by the project team.

Following multidisciplinary stakeholder meetings and the brainwriting premortem exercise, we constructed the first of 14 low-fidelity prototypes. These prototypes were presented on paper to stakeholders for feedback and revision. The EHR application analysts building this tool provided guidance regarding the capabilities and limitations of the existing EHR functionality.

Using the final low-fidelity prototype produced, the Discharge Today tool was constructed in the test EHR environment (Figure

1). We convened “think-aloud” sessions with users from the Division of Hospital Medicine for two purposes. First, we asked users to interact with the tool following minimal instructions and using a modified cognitive task analysis approach [38], while we made note of challenges users encountered or questions asked. This information was used to inform both revisions made to the tool and instructions developed for users. Second, we asked users to talk about their perceptions of the tool, specifically its utility and usability, as they interacted with the tool. This feedback informed modifications made to the tool. Following these sessions, we transitioned to “near-live” testing, in which we conducted preproduction user testing with both hospital medicine providers and ancillary department staff using real patient data and updated instructions. The purpose of this testing was to identify any components of the tool that were not functioning as intended prior to transitioning to the pilot test.

Following any changes or additions to the Discharge Today tool, functionality testing took place in the test EHR environment with a secondary validation stage in a shadow EHR environment with real patient data on a set delay. In addition, the end users each tested any revision or addition to the functionality in the test EHR environment prior to moving updates to production. Monitoring of the functionality of the tool occurred via periodic testing of the tool in both the test EHR environment and the production environment to isolate issues with the tool that were not otherwise identified prior to the go-live phase. In addition, feedback was solicited from end users to identify issues that became apparent during clinical work. We approached clinical staff in their workplaces to obtain real-time feedback on the functionality of the tool.

Surveys were conducted following the final month of the pilot phase using Research Electronic Data Capture (REDCap), a secure, web-based application for building and managing web-based surveys and databases [39]. Physicians, advanced practice providers, nurses, care management staff, and other clinical staff were asked to complete surveys regarding the usability of the Discharge Today tool and their experience with it. The factors chosen for evaluation, including time required to use the tool, accuracy of data collected via the tool, and helpfulness of the tool, were selected based on stakeholder feedback from both providers and other clinical staff.

Figure 1. Final low-fidelity prototype prior to EHR development and the Discharge Today tool (demonstration only, no protected health information).

Epic Discharge Radio Button Tool

Allow for dynamic changes, tracking over time, and a feedback loop so team knows task is completed.

| Patient name/age/sex | MRN | Room | Service | DC Today? | First Call |
|----------------------|--------|------|------------|--|----------------------|
| Smith/40/F | 123456 | 1102 | Medicine 1 | <input checked="" type="checkbox"/> Definite (before midnight) <input type="checkbox"/> Possible (24-48 hrs) <input type="checkbox"/> No (>48 hrs) | Burden: 720-848-4289 |
| Doe/32/M | 789101 | 1104 | Medicine 1 | <input type="checkbox"/> Definite (before midnight) <input checked="" type="checkbox"/> Possible (24-48 hours) <input type="checkbox"/> No (>48 hrs) | Burden: 720-848-4289 |

Floating flowsheet rows

If Definite selected:

Before 11 am
 Before 2 pm
 After 2 pm

If Definite or Possible selected:
 What are you waiting on (check all that apply)?

IR
 Echo
 PT
 OT
 SLP
 Cath lab
 Glucose Management Team
 Pharmacy OPAT
 RT home o2
 ID consult

Note _____

Option 1. Push DC Today? status with task needed & date time/stamp to PAF column with added floating flowsheet row to document follow-up.

Option 2. If 'Definite' selected, push notification for PT, OT, and SLP to rehab therapy pager with distinct messages for each individual area.

1) Populate barrier within care progression report with active notification of updates to report.

2) Populate work queue with all possible/definite patients and what we are waiting on for Discharge Team.

1. Click in "D/C Today? Primary" column of the EHR worklist

| Patient Name/Age/Gender | Patient Location | Attending | Service | D/C Today? Primary |
|-------------------------|------------------|-----------------|----------|--------------------|
| Schmo, Joe/45/M | Med/Surg Unit | Test, Doctor MD | Medicine | DC Today |
| Smith, Jane/60/F | Med/Surg Unit | Test, Doctor MD | Medicine | Definite |
| Miller, Pete/54/M | Med/Surg Unit | Test, Doctor MD | Medicine | Possible |
| Rodriguez, Mary/35/F | Med/Surg Unit | Test, Doctor MD | Medicine | Definite |
| Adams, John/71/M | Med/Surg Unit | Test, Doctor MD | Medicine | Tomorrow |
| Baker, Sue/48/F | Med/Surg Unit | Test, Doctor MD | Medicine | In 24-48 hours |

2. Document discharge readiness and discharge needs

Patient Discharge Today?

Discharge Today? Definite Possible Tomorrow In 24-48 hours >48 hours

When will the patient be ready for DC? Before 11 AM Before 2 PM After 2 PM

What are you waiting on?

DMF DME Echo IR PCC Line placement Pharmacy Rehab PT OT Speech Dripys
 Follow-up Appointment Placement Social Work/Care Management Transportation
 Medical Improvement Test Results (Lab, Radiology) Wound Care

What consults are you waiting for?

Cardiology Endocrine GI Therapeutics Hematology ID Consult Oncology Pulmonary Renal
 Rheumatology Other consultant not listed

3. Disseminate discharge readiness and pending tasks throughout the EHR work space used by clinicians

D/C Today Partner View

| Service | Location | Single DC Today P/U | Single DC Today | Single DC Today | What are you waiting on? | Care Progression Report |
|----------------------|----------|---------------------|-----------------|-----------------|------------------------------------|--|
| Medicine 1 | 120642 | DC Today | DC Today | DC Today | What are you waiting on? | Provider Identified Needs for Discharge |
| Medicine 1 | 833781 | DC Today | DC Today | DC Today | What are you waiting on? | Most Recent Value |
| Acute Care Elderly 1 | 878081 | DC Today | DC Today | DC Today | What are you waiting on? | Discharge Today? Definite Filed at 07/12/2020 1432 |
| Hospitalist 1 | 120642 | DC Today | DC Today | DC Today | What are you waiting on? | When will the patient be ready for DC? Definite Filed at 07/12/2020 1432 |
| Acute Care Elderly 1 | 833781 | DC Today | DC Today | DC Today | What consults are you waiting for? | What are you waiting on? DME Filed at 07/12/2020 1432 |

4. Alert providers that action has been taken via feedback loop mechanism embedded within EHR



Results

During the Discover and Define stage of development, applying the analytic-deliberative model, we engaged with 20 different stakeholders in 28 separate meetings across disciplines and settings, including care managers, nurse managers, patients and caregivers, an established, university-based patient advisory panel, and EHR builders and consultants. We also met several

times with clinical directors, advanced practice providers, and physicians from departments of hospital medicine, infectious diseases, cardiology, endocrinology, hematology, pulmonary/critical care, and nephrology. Finally, we met multiple times with clinical staff and managers from respiratory therapy, rehabilitation services (specifically occupational, physical, and speech therapy), interventional radiology, pharmacy, glucose management, echocardiography, the heart and vascular team, and dialysis (Table 1).

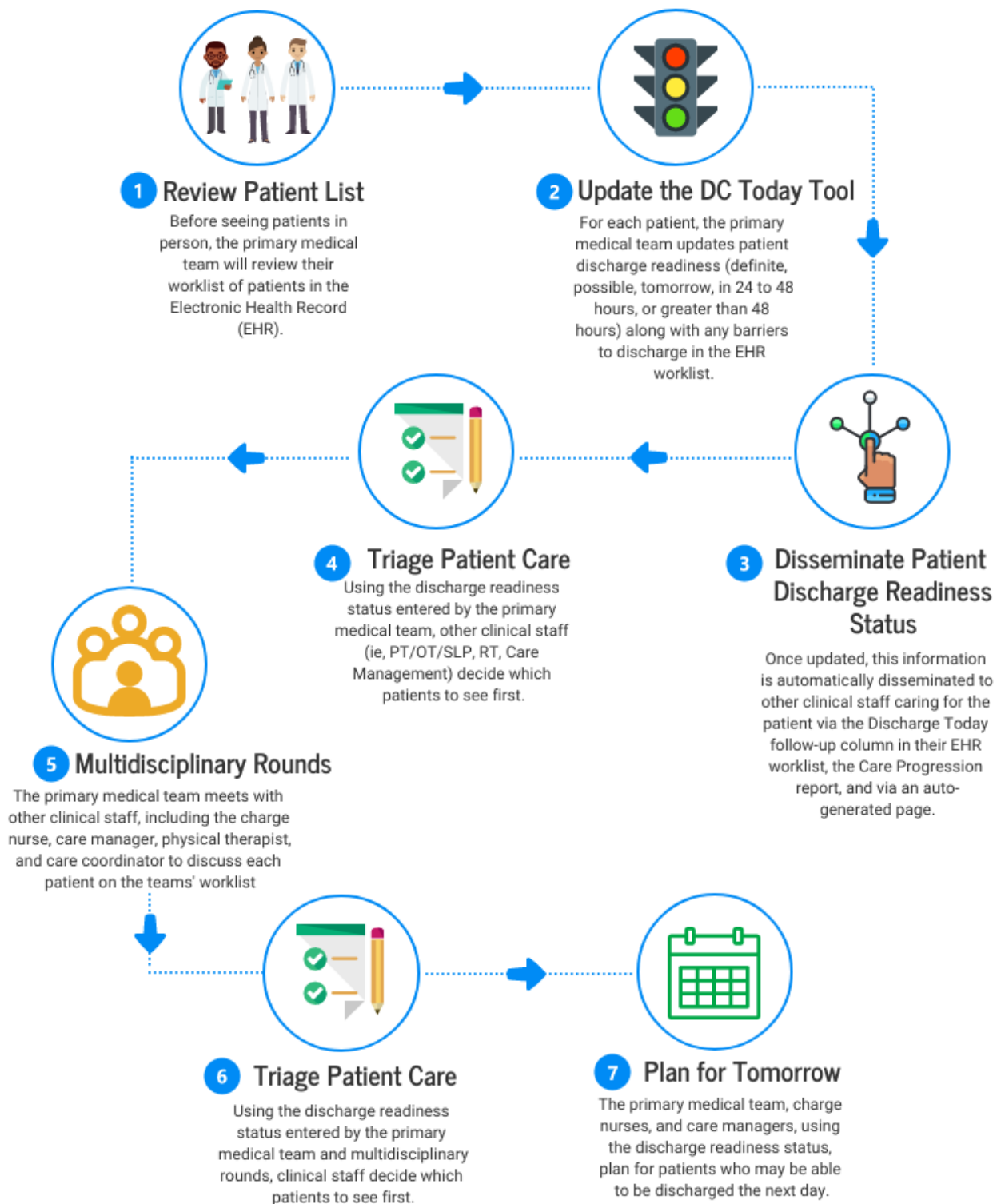
Table 1. Key stakeholders and their engagement activities.

| Key stakeholders | Engagement activities |
|---|--|
| Patients | <ul style="list-style-type: none"> • 1 Patient Advisory Panel meeting • 10 telephone conversations |
| Hospital medicine providers | <ul style="list-style-type: none"> • 2 lunch meetings • 1 avoidable delay survey • 1 user testing session • 2 usability and experience surveys |
| Nursing staff | <ul style="list-style-type: none"> • 2 meetings • 2 usability and experience surveys |
| Case management/social work staff | <ul style="list-style-type: none"> • 2 meetings • 1 usability and experience survey |
| Physical therapy/occupational therapy/speech-language pathology staff | <ul style="list-style-type: none"> • 3 meetings • 1 usability and experience survey |
| Glucose management team members | <ul style="list-style-type: none"> • 1 meeting |
| Pharmacy staff | <ul style="list-style-type: none"> • 2 meetings • 1 usability and experience survey |
| Respiratory therapy staff | <ul style="list-style-type: none"> • 3 meetings • 1 usability and experience survey |
| Echocardiography staff | <ul style="list-style-type: none"> • 2 meetings |
| Interventional radiology staff | <ul style="list-style-type: none"> • 1 meeting |
| Department of Medicine clinical directors | <ul style="list-style-type: none"> • 1 meeting |
| Infectious disease staff | <ul style="list-style-type: none"> • 2 meetings |
| Cardiology staff | <ul style="list-style-type: none"> • 1 meeting |
| Endocrinology staff | <ul style="list-style-type: none"> • 1 meeting |
| Hematology staff | <ul style="list-style-type: none"> • 1 meeting |
| Pulmonary services staff | <ul style="list-style-type: none"> • 1 meeting |
| Renal medicine staff | <ul style="list-style-type: none"> • 1 meeting |

During these meetings, we discussed the stakeholders' experiences with the discharge process, what went well and what could be improved, and their current workflow related to discharge. We observed clinical staff interacting with the EHR to map how different staff providing care to patients used EHR functionalities and how the Discharge Today tool might best

be integrated. Using the information gathered during conversations with and observation of stakeholders, we constructed a user journey to illustrate how the Discharge Today tool might best be integrated with existing workflows and what might be changed ([Figure 2](#)).

Figure 2. User journey of the patient discharge workflow. DC Today: Discharge Today; OT: occupational therapy; PT: physical therapy; RT: respiratory therapy; SLP: speech-language pathology.



To work as designed, using guidance provided by the stakeholders involved in our user-centered design process, we developed a framework for our Discharge Today tool, encompassing the following functions and operational processes. First, the tool must populate a list of patients with information from designated data sources and display the results on a user interface dashboard for provider access. Second, the tool must be accessible from the customizable patient worklist available

in the provider workflow whenever a provider logs into the EHR. Third, the discharge readiness status for each patient on a provider's list must be displayed with color-coding (green if the patient is a definite discharge with a discharge order, yellow if the patient is a definite discharge without a discharge order, orange if the patient is a possible discharge this day, blue if the patient could go home tomorrow, red if the patient is not going home this day, and gray if the patient is expected to go home

in the next 24 to 48 hours). Fourth, data collected from primary team providers each morning via the Discharge Today tool must be pushed automatically through three different processes that are integrated seamlessly with existing clinical workflows: the EHR patient worklists via the Discharge Today follow-up column, the Care Progression report, and an auto-generated page. Finally, through a feedback mechanism implemented such that when staff from ancillary departments such as respiratory therapy (RT), physical therapy (PT), occupational therapy (OT), and speech-language pathology (SLP) document patient care in the EHR using their standard workflow, the primary team provider who originally reported a requirement from these ancillary departments must be alerted that something has changed, creating a feedback loop within the EHR. To alert providers using the Discharge Today tool, an icon indicating new information is populated in the Discharge Today tool column displayed in the provider's list. Combining this functionality creates a tool that enables real-time communication among care team members via the EHR.

All data collected by the Discharge Today tool are stored in the transactional database of the EHR at the level of the patient

hospital encounter. This supports real-time use, functional processes, and dashboard population. The tool populates a list of patients managed by individual providers with patient attributes, encounter attributes, provider attributes, and discharge readiness status, timing, and barriers into a user interface dashboard. Providers interact with their patient list in the dashboard and make item entries for each patient from structured category lists (Table 2). The data entered into the tool by the primary team provider populate the "Provider Identified Needs for Discharge" section of the Care Progression report used by providers, nursing staff, and care management staff to view the overall care of the patient during the hospitalization. The data entered also autopopulate a Discharge Today Follow-up column that is used as part of the provider's patient worklists by consulting teams (eg, cardiology, endocrine, and gastrointestinal) and ancillary services (eg, RT, pharmacy, OT, PT, SLP, and wound care). Finally, for OT, PT, and SLP, an autogenerated page is sent that is populated with patient and discharge barrier data when a patient is identified as a definite discharge waiting on a final evaluation from these services.

Table 2. Discharge Today data elements and sources in the electronic health record.

| Data element | Data source/location |
|----------------------------------|--|
| Patient attributes | Patient record |
| Encounter attributes | Hospital encounter record |
| Provider attributes | Provider record |
| Discharge probability categories | Transactional database tables |
| User interface highlight colors | Code extension |
| Discharge timing categories | Transactional database tables |
| Discharge barriers | Transactional database tables/alert criteria |
| Discharge follow-up comments | Transactional database tables |

During the Develop and Deliver phase, from March 5 to July 31, 2019, we conducted iterative development, testing, and optimization of the Discharge Today tool while in use by Hospital Medicine advanced practice providers and physicians. During this phase, stakeholders requested 46 modifications, with 85% of these requests occurring in the first two months of the pilot study. Of the 46 modifications, 11 (24%) were set aside

due to existing limitations in EHR functionality, and 10 (22%) were considered to have insufficient utility or potential for overdesign and were thus not pursued. A total of 25/46 modifications (54%) were successfully executed, and 3 of the 25 modifications (12%) were fully implemented after the end of the pilot period (Table 3).

Table 3. Modifications to the Discharge Today tool (N=25).

| Date requested (2019) | Request | Date fully modified (2019) |
|-----------------------|---|----------------------------|
| March 7 | Rename columns to help with clarity when providers are wrenching them in | March 8 |
| March 11 | If a provider reselects “possible,” “definite,” or “no,” reset the branching logic | March 14 |
| March 17 | PT ^a /OT ^b /SLP ^c pages are sent out when selected, with lockout if more than one page is selected within 12 hours | March 8 |
| April 1 | Update names of columns to be less confusing for wrenching in or display in larger patient lists | April 8 |
| March 5 | Add Transportation as a barrier | April 12 |
| March 6 | Add PICC ^d Line Placement as a barrier | April 12 |
| March 8 | Add a way to indicate future discharge (ie, in 24-48 hours) | April 12 |
| March 12 | Add DME ^e as a barrier | April 12 |
| March 12 | Update RT ^f barrier to Home O ₂ | April 12 |
| March 12 | Update the Social Work barrier to Social Work/Care Management | April 12 |
| March 12 | Add “Other consultant not listed” as a barrier | April 12 |
| March 12 | Update pager system to allow a page once every 12 hours | April 12 |
| April 19 | Combine PT and OT pager numbers | April 26 |
| April 24 | Indicate in the page set to PT/OT which discharge selection was made (“Possible” or “Definite”) | April 26 |
| March 11 | Reset column after 3 days | May 23 |
| March 11 | Automatically update to definite (green) when a discharge order is placed | May 23 |
| April 11 | Change the order of the barrier selections | May 23 |
| April 12 | New column to display barrier selections from the Discharge Today Primary column | May 23 |
| April 12 | Make the “In 24-48 hours” selection gray in color | May 27 |
| March 5 | Develop a feedback loop | June 24 |
| April 26 | Add Test Results (Laboratory, Radiology) as a barrier | June 27 |
| June 14 | Add Wound Care as a barrier | June 27 |
| May 7 | Add fields to capture more information about PT/OT barriers | July 30 |
| July 2 | Change “No” to “>48 hours” | September 27 |
| March 15 | Add option to select for anticipated discharge tomorrow | December 3 |

^aPT: physical therapy.

^bOT: occupational therapy.

^cSLP: speech-language pathology.

^dPICC: peripherally inserted central catheter.

^eDME: durable medical equipment.

^fRT: respiratory therapy.

We found that most providers who responded to the usability and experience survey (21/24, 88%) reported that the tool either shortened or did not change the amount of time required to complete the discharge workflow. Of the nursing, care management, and other clinical staff surveyed who reported using the Discharge Today tool during the pilot study (34/67, 51%), all felt that the tool either shortened or did not change the amount of time required to complete their workflows. In

addition, a majority of ancillary staff who completed the survey reported that they believed that hospitalists were updating the discharge information (26/34, 77%), that the information was accurate (22/34, 65%), and that the information was helpful (32/34, 94%). These data suggest that the Discharge Today tool was successfully adopted by providers and other clinical staff (Table 4).

Table 4. Provider (n=24) and clinical staff (n=67) responses to the survey on usability and experience of the Discharge Today tool following the pilot implementation period.

| Question | Response, n (%) |
|---|-----------------|
| Providers (n=24) | |
| Please select the ways in which you used the discharge tool (check all that apply). | |
| Entered/updated discharge information in patient list column | 21 (88) |
| Viewed discharge information in patient list column | 13 (54) |
| Viewed discharge information in the care progression report | 3 (13) |
| Determine order of rounds, prioritizing early discharges | 1 (4) |
| For what percentage of your patients did you use the tool? | |
| 0%-25% | 0 (0) |
| 26%-50% | 5 (21) |
| 51%-75% | 3 (13) |
| 76%-100% | 16 (67) |
| When did you utilize the tool the most? | |
| Beginning of shift | 21 (88) |
| Middle of shift | 5 (21) |
| End of shift | 6 (25) |
| How did the tool affect your discharge workflow? | |
| Saved time | 6 (25) |
| Added time | 3 (13) |
| Did not change | 15 (63) |
| Clinical staff (n=67) | |
| Did you use the Discharge Today – Follow-up Ancillary/Consultant tool over the last month? | |
| Yes | 34 (51) |
| No | 33 (49) |
| Please select the ways in which you used the discharge tool. | |
| Viewed discharge information in my clinical workflow | 31 (91) |
| Contacted hospitalist who entered information in Epic | 5 (15) |
| Viewed discharge information in the care progression report | 14 (41) |
| Do you feel hospitalists are completing and updating the discharge information? | 26 (77) |
| Did you find the information accurate? | 22 (65) |
| Did you find the information helpful? | 32 (94) |
| How did the tool affect your discharge workflow? | |
| Saved time | 21 (62) |
| Added time | 0 (0) |
| Did not change | 13 (38) |
| Do you find the tool helpful? | 31 (91) |
| What prevented you from using the tool? | |
| Discharge information not completed by hospitalists | 6 (18) |
| Information not updated/accurate | 7 (21) |
| Lack of time | 5 (15) |
| Lack of knowledge | 20 (61) |
| Forgot/overlooked | 3 (9) |

| Question | Response, n (%) |
|--------------|-----------------|
| Chose not to | 1 (3) |
| Other | 4 (12) |

We also collected qualitative usability and experience data from hospital medicine providers and clinical staff following the pilot implementation period using open-ended questions in the REDCap survey. Themes were derived from responses provided to five open-ended questions included in the survey. Free text responses were coded, and a synthesis of the results emerging

from the responses to each of the open-ended questions was summarized (Table 5).

Responses were categorized into five themes, namely efficiency, integration into workflow, redundancies avoided, expedited communication, and patient-centered outcomes. The data provided both positive feedback and opportunities for improvement.

Table 5. Qualitative usability and experience data from hospitalists and other clinical staff following pilot implementation of the Discharge Today tool.

| Theme | Quotes | |
|---------------------------|--|---|
| | Positive feedback | Opportunities for improvement |
| Efficiency | <p>“Noticed quick responses from PT/OT for evaluation which expedited discharge.”</p> <p>“I think it is quick and hopefully as all ancillary staff learn to utilize it can continue to improve discharge times.”</p> | <p>“Not all teams are utilizing the tool yet.”</p> |
| Integration into workflow | <p>“Well integrated into my existing workflow.”</p> | <p>“Sometimes the options available to explain what is holding up a discharge does not apply...would be nice to have an “other” comment box.”</p> |
| Avoidance of redundancy | <p>“In theory, it should avoid redundancies and emphasize the hold up to discharges...If nurses know we are consistently updating this it would help eliminate unnecessary pages.”</p> | <p>“Other services/staff learning to utilize it in their workflows.”</p> <p>“Some ancillary services are still utilizing old workflows.”</p> |
| Expedited communication | <p>“It is nice to be able to state what would be potentially holding up the discharge and not have to call those services/departments directly.”</p> | <p>“A little more feedback about what is happening as we click these things (like a little small font blurp).”</p> |
| Patient-centered outcomes | <p>“Per the DC tool knew [the patient was] going to be going home in the next day or two. I was able to decide on a DC plan and send the prescriptions to the pharmacy for fill. Low [<i>sic</i>] and behold, the insulin prescribed was not covered so we were able to revise the plan well before day of DC therefore avoiding a delay.”</p> | <p>“Would it be possible that a checklist could be given to the patient? Allowing patient to follow the process...an opportunity to ask questions?”</p> |

Discussion

The important findings of this work are (1) providers, hospital clinical staff, and patients are willing to serve as stakeholders to help guide the user-centered design of an EHR-based tool and (2) stakeholder engagement during preimplementation, throughout implementation, and into postimplementation results in positive feedback and substantial adoption by clinical staff.

We applied communication theory to the design of this tool with the intent of fostering interdisciplinary discharge communication and teamwork. Communication across care teams and improved interdisciplinary care has been recognized as an important factor for high-quality patient-centered care and for high-functioning teams. Studies have shown that when care teams communicate better, efficiency outcomes are improved [18]. Patients have also expressed a need for the clinical staff caring for them to communicate with each other more effectively [40].

Studies exploring the use of the EHR for discharge planning have been limited to static electronic reports constructed from

EHR data elements, including barriers to discharge documented at admission, care management data, and discharge criteria [19], or other targeted interventions, such as improving discharge summaries for patients or medication reconciliation at discharge [20,21,32,41]. In contrast, our Discharge Today tool was designed to capture and disseminate patient discharge readiness in a real-time, dynamic way, as opposed to merely reporting static discharge information via standard report functionality.

Tyler et al [19] reported developing and implementing an EHR-based discharge readiness report for medical and medical subspecialty patients that provides a summary of information related to patient discharge. As with our tool, this report was easily accessible and readily adopted by clinical staff. Researchers from the University of Wisconsin Hospital and Clinics described designing an EHR-based discharge summary template that was successfully adopted by clinicians hospital-wide [21]. Similar to these other projects designed to improve discharge communication and workflow, our Discharge Today tool was readily adopted by both providers and other clinical staff.

Although common quality improvement tactics, such as identifying champions, Plan-Do-Study-Act cycles, and process mapping, are valuable tools, developing and implementing HIT innovations necessitates frameworks and methods that are specifically designed for HIT. To engage hospitalists, nurses, other clinical staff, patients, families and caregivers, and hospital leadership, we met with 20 different stakeholder groups to obtain feedback about the design and functionality of the tool. Following this engagement process, we made improvements, implemented a pilot tool, and assessed discharge processes and both provider and clinical staff experience with the tool. To guide the development and implementation of our pilot Discharge Today tool, we chose to apply the analytic-deliberative model of stakeholder engagement [33] and the Chokshi and Mann process model for user-centered digital development [35].

Our approach to stakeholder engagement and user-centered design had a number of strengths. We deliberately, proactively applied established frameworks to guide both our stakeholder engagement process and the process of designing our tool. In addition, we leveraged existing functionality in our EHR to create an innovative discharge communication tool based on a design framework developed in collaboration with our stakeholders. Finally, this discharge communication tool facilitates real-time communication across hospital clinical staff,

reducing reliance on static communication tools or interruptions to clinical care.

Our approach had a few limitations. We were unable to identify stakeholders in every clinical area of the hospital with whom communication about patient discharge readiness or barriers may occur. In addition, limitations to functionality of the EHR at the time of the development of this tool restricted the development of feedback loops to discharge barriers related to physical therapy, occupational therapy, speech therapy, and respiratory therapy rather than across all clinical areas. We continue to work with hospital leadership to fully integrate the Discharge Today tool with other initiatives implemented to improve discharge processes, improve patient flow, and alleviate capacity problems. Finally, as this tool expands in scale, future work will begin to assess how this type of tool (and future modifications thereof) affects quality measures such as patient experience, teamwork, and potentially readmissions.

By using a deliberate and collaborative stakeholder engagement process, we obtained commitments from numerous key stakeholders to participate in the design and testing of our EHR discharge readiness tool. The tool has been implemented for clinical use, and we have conducted an extensive evaluation of the implementation and effectiveness of the tool from a multistakeholder perspective. Survey data collected from Hospital Medicine providers and ancillary clinical staff suggest that the tool has been successfully adopted by clinical staff.

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Conflicts of Interest

None declared.

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Abbreviations

- EHR:** electronic health record
- HIT:** health information technology
- OT:** occupational therapy
- PT:** physical therapy
- REDCap:** Research Electronic Data Capture
- RT:** respiratory therapy
- SLP:** speech-language pathology

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Review

Augmenting Critical Care Patient Monitoring Using Wearable Technology: Review of Usability and Human Factors

Evismar Andrade^{1,2}, BSc; Leo Quinlan^{2,3}, PhD; Richard Harte^{1,2}, PhD; Dara Byrne^{4,5}, MD; Enda Fallon⁶, MEngSc; Martina Kelly⁶, PhD; Siobhan Casey⁷, MSc; Frank Kirrane⁸, MSc; Paul O'Connor^{4,5}, PhD; Denis O'Hora⁹, PhD; Michael Scully^{10,11}, MD; John Laffey^{10,11}, MD; Patrick Pladys^{12,13}, PhD, MD; Alain Beuchée^{12,13}, PhD, MD; Gearoid ÓLaighin^{1,2}, PhD

¹Electrical & Electronic Engineering, School of Engineering, National University of Ireland, Galway, Galway, Ireland

²Human Movement Laboratory, CÚRAM Centre for Research in Medical Devices, National University of Ireland, Galway, Galway, Ireland

³Physiology, School of Medicine, National University of Ireland, Galway, Galway, Ireland

⁴General Practice, School of Medicine, NUI Galway, Galway, Ireland

⁵Irish Centre for Applied Patient Safety and Simulation (ICAPSS), University Hospital Galway, Galway, Ireland

⁶Mechanical Engineering, School of Engineering, NUI Galway, Galway, Ireland

⁷Intensive Care Unit, University Hospital Galway, Galway, Ireland

⁸Medical Physics and Clinical Engineering, University Hospital Galway, Galway, Ireland

⁹School of Psychology, NUI Galway, Galway, Ireland

¹⁰Anaesthesia, School of Medicine, NUI Galway, Galway, Ireland

¹¹Department of Anaesthesia & Intensive Care Medicine, Galway, Ireland

¹²Centre Hospitalier Universitaire de Rennes (CHU Rennes), Rennes, France

¹³Faculté de Médecine de l'Université de Rennes, Rennes, France

Corresponding Author:

Leo Quinlan, PhD

Human Movement Laboratory

CÚRAM Centre for Research in Medical Devices

National University of Ireland, Galway

University Road

Galway

Ireland

Phone: 353 9149 ext 3710

Fax: 353 91 494544

Email: leo.quinlan@nuigalway.ie

Abstract

Background: Continuous monitoring of the vital signs of critical care patients is an essential component of critical care medicine. For this task, clinicians use a patient monitor (PM), which conveys patient vital sign data through a screen and an auditory alarm system. Some limitations with PMs have been identified in the literature, such as the need for visual contact with the PM screen, which could result in reduced focus on the patient in specific scenarios, and the amount of noise generated by the PM alarm system. With the advancement of material science and electronic technology, wearable devices have emerged as a potential solution for these problems. This review presents the findings of several studies that focused on the usability and human factors of wearable devices designed for use in critical care patient monitoring.

Objective: The aim of this study is to review the current state of the art in wearable devices intended for use by clinicians to monitor vital signs of critical care patients in hospital settings, with a focus on the usability and human factors of the devices.

Methods: A comprehensive literature search of relevant databases was conducted, and 20 studies were identified and critically reviewed by the authors.

Results: We identified 3 types of wearable devices: tactile, head-mounted, and smartwatch displays. In most cases, these devices were intended for use by anesthesiologists, but nurses and surgeons were also identified as potentially important users of wearable technology in critical care medicine. Although the studies investigating tactile displays revealed their potential to improve clinical

monitoring, usability problems related to comfort need to be overcome before they can be considered suitable for use in clinical practice. Only a few studies investigated the usability and human factors of tactile displays by conducting user testing involving critical care professionals. The studies of head-mounted displays (HMDs) revealed that these devices could be useful in critical care medicine, particularly from an ergonomics point of view. By reducing the amount of time the user spends averting their gaze from the patient to a separate screen, HMDs enable clinicians to improve their patient focus and reduce the potential of repetitive strain injury.

Conclusions: Researchers and designers of new wearable devices for use in critical care medicine should strive to achieve not only enhanced performance but also enhanced user experience for their users, especially in terms of comfort and ease of use. These aspects of wearable displays must be extensively tested with the intended end users in a setting that properly reflects the intended context of use before their adoption can be considered in clinical settings.

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KEYWORDS

patient monitor; physiologic monitor; human factors; ergonomics; usability; user experience; wearable; mobile phone; critical care

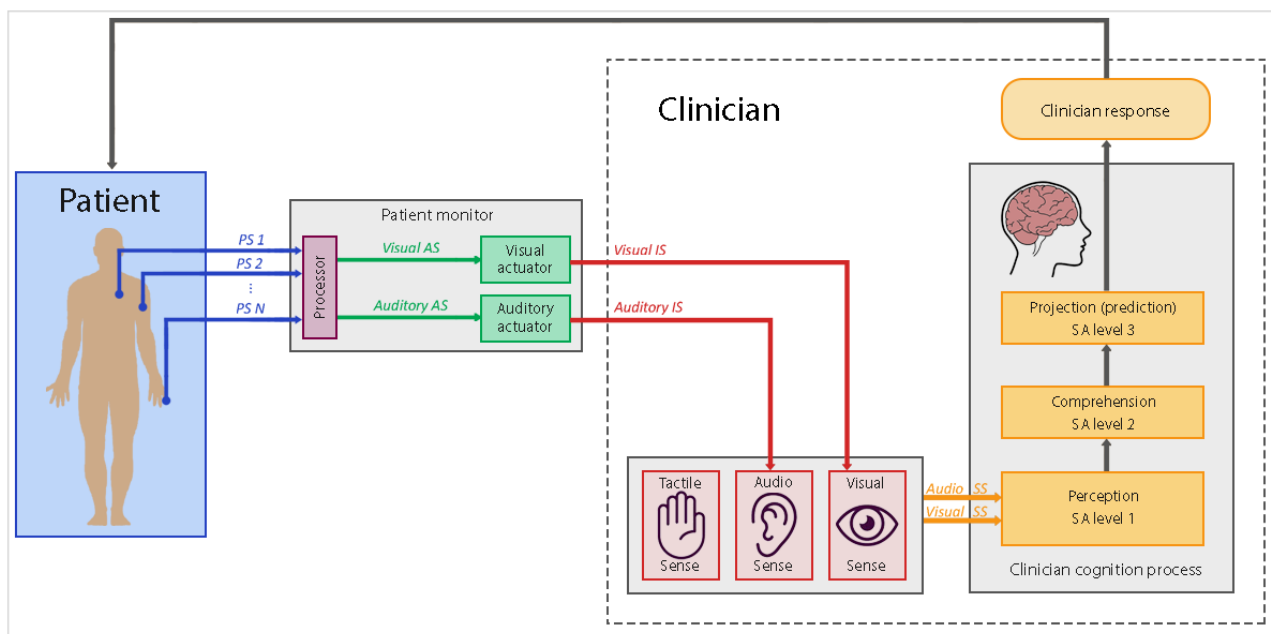
Introduction

Challenges in Critical Care Patient Monitoring

Monitoring the vital signs of patients is a crucial task when dealing with critical care patients [1,2]. For this task, critical care clinicians extensively use a patient monitor (PM), which is typically placed close to the patient in the intensive care unit (ICU) or operating room. The essential features of a PM used for critical care patient monitoring were presented by Andrade et al [3]. The PM uses sensors connected to the patient to

measure a range of *physiological signals* (eg, heart rate [HR], blood pressure [BP], and saturation of peripheral oxygen [SpO₂]). This information is processed, converted into a human-readable format (eg, digital values and traces), and presented to the clinician through the PM screen. In addition, when the PM detects any sign of abnormality in the patient's vital signs (eg, elevated HR), it alerts the user of the potential risk to the patient through the auditory alarm system. These interaction mechanisms between the PM and the clinician are presented in Figure 1.

Figure 1. Patient monitor interaction mechanisms with the clinician. The patient's physiological state is conveyed to the clinician through their visual and auditory senses. Once the clinician perceives a change in the patient's state through these sensory signals, their cognition processes make use of this information (in addition to other contextual information) to comprehend the patient's current state and make projections of their future state. At the end of this process, clinicians can make a decision on what they should do next regarding the patient's care. AS: actuator signal; EDS: external device signal; IS: interaction signal; PS: physiological signal; SS: sensory signal.



These interaction processes enable the clinician to be continually informed about the patient's state. As discussed by Andrade et al [3], the PM is used in a variety of critical care settings (eg, ICUs, high dependency units, and operating theaters). Each of these different settings puts different demands on the PM, and

although this device is designed as a generic patient monitoring device, some challenges are associated with using the PM to monitor critical care patients in some specific contexts of use. For example, during an anesthesia procedure, anesthesiologists need to check the patient's skin pallor, chest movement, and

other signs, while also continuously being required to check the PM for the patient's vital signs [4,5]. In this case, the clinician's *visual sense* is required for several tasks simultaneously, which increases the likelihood of the clinician missing a critical event. This can be even more problematic when, because of limited space, the PM is not in the anesthesiologist's direct line of vision [6]. This ergonomic issue not only impacts the anesthesiologist's physical comfort but can also lead to human error [7].

Another well-documented context-of-use challenge for a PM is the noise generated by PM alarms and the associated alarm fatigue [8,9]. ICU nurses, for example, may be exposed to as many as 700 alarms (from multiple alarming medical devices) per patient per day [10,11]. In addition, depending on the ICU layout, multiple patients might be monitored in the same area, which increases the number of alarms significantly. As the ICU nurse must be notified immediately if the vital signs become abnormal, they must be close enough to the PM to be able to hear an alarm. This cacophony of alarms may disturb their workflow and distract them, especially in situations where they are already under stress or involved in other essential activities related to the patient's care [12].

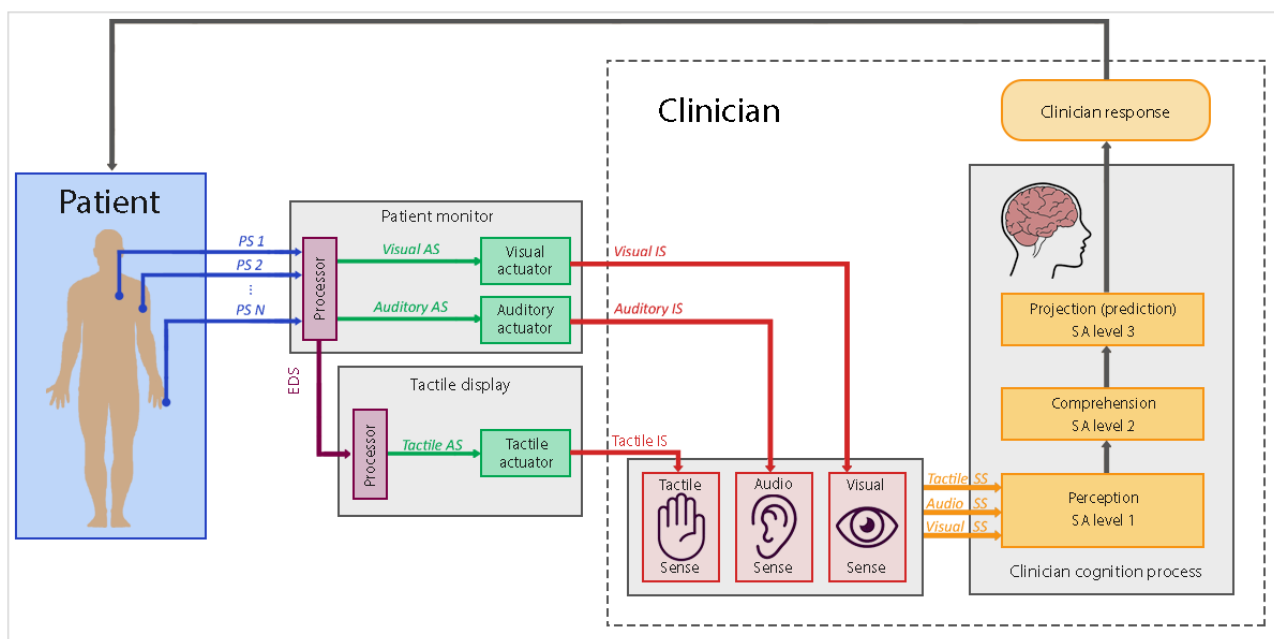
In an attempt to improve patient monitoring in critical care, several researchers have developed novel interface designs to

augment the PM [3]. In other studies, researchers have attempted to minimize the problem of alarm fatigue with various techniques such as developing better signal filtering algorithms, changing the PM settings, and changing hospital protocols (eg, frequently changing electrocardiogram electrodes, which might otherwise lose contact because of poor adhesiveness) [13]. With the advancement of wearable technology in a range of application areas, researchers have sought to investigate how wearable devices may be used to enhance patient monitoring by overcoming these identified problems and thus potentially improve the experience of the clinicians and, therefore, potentially enhance their performance. Our review focuses on the use of wearable devices to address the identified problems associated with the PM in critical care medicine.

Augmenting Patient Monitoring With Tactile Displays

As illustrated in Figure 1, the PM conveys patient information to clinicians visually and aurally. Tactile displays, on the other hand, are composed of small devices (tactors) that use vibratory sequences to display the patient status to the clinician. Therefore, the goal of tactile displays is to enhance the patient monitoring task by using the clinician's *tactile sense* in addition to their *visual* and *audio* senses, which are already being used by the PM (Figure 2).

Figure 2. When a tactile display augments a patient monitor, the tactile display receives the patient data from the patient monitor, and this information is conveyed to the clinician using the clinician's tactile sense through the delivery of vibration sequences. Tactile displays can be attached to different parts of the clinician's body, such as the wrist, forearm, and waist. AS: actuator signal; EDS: external device signal; IS: interaction signal; PS: physiological signal; SS: sensory signal.



In addition to information coding using the vibration time sequences, designers may also use the intensity of the vibration and the position of the tactors as means to display additional information. For example, the intensity of the vibration can be used to convey the extent of a change in a variable value with a low amplitude change encoded as a low-intensity vibration and a high amplitude change encoded as a high-intensity vibration. The location of the tactors can be used to represent the relative value of a variable (eg, tactors vertically positioned in the arm can be programmed to indicate an increase or

decrease in the variable value by activating the tactors in sequence upwards or downwards) and to represent a specific physiological measure (eg, a tactor on the left arm representing SpO₂ and a tactor on the right arm representing HR) [14]. Therefore, designers can use a series of combinations and permutations with tactile parameters to display patient information.

The tactile display uses a *processed* version of the data presented by the PM screen. For example, it might display whether a

particular physiological signal is increasing, decreasing, or not changing (*continuous display*), or it can be used to display alarms in a modified way to that delivered aurally by the PM (*alarm display*). Continuous tactile alarm displays could be used to support the anesthesiologist during anesthesia procedures by informing the anesthesiologist of the patient’s state without having to avert their eyes from the patient multiple times during a procedure. When configured as an alarm display, the vibration pattern delivered by the tactor may indicate a PM alarm status (eg, low risk, high risk, or technical alarm), and the body site of the vibration could indicate which parameter is the subject of the alarm. The anesthesiologist could use this tactile display configuration to be informed only when a variable value becomes abnormal, without having to look at the PM screen to establish which variable is generating the alarm. ICU nurses could also use alarm tactile displays to reduce the number of audio alarms in the ICU. For example, instead of the PM sounding an alarm to everyone in the ICU, alarms would be silently directed to the nurse looking after that particular patient, using a tactile display.

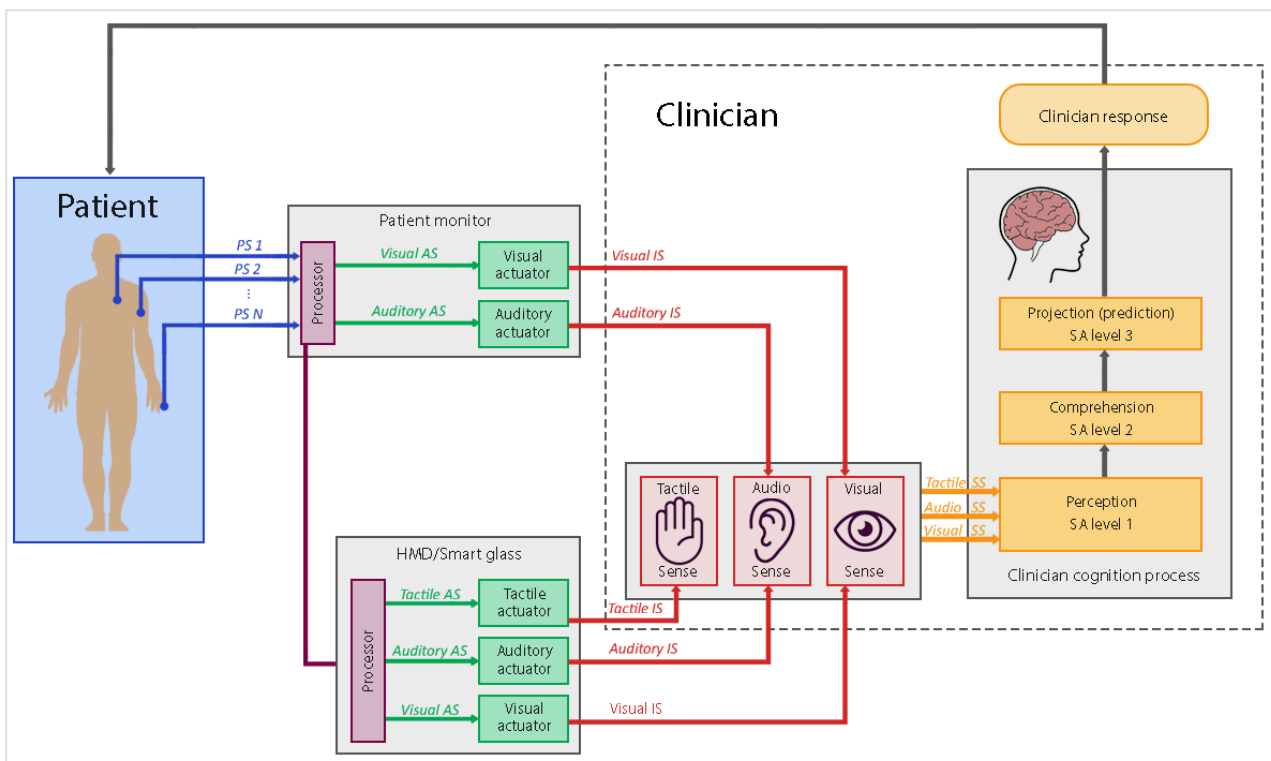
Augmenting Patient Monitoring With Head-Mounted Displays

Another approach to solving the problem of anesthesiologists having to divert their visual attention from the patient to the

PM screen is the use of head-mounted displays (HMDs). The patient’s vital signs can be displayed directly on the HMD, allowing the anesthesiologist to observe the vital signs regardless of where their gaze is directed. Designers have the option to display the same information presented by the PM screen or provide a subset of that information (eg, only the digital values).

The initial HMDs were bulky prototypes with a wired connection to a computer. However, in 2013, the first smart glass was launched, Google Glass (Google LLC). This device is an optical HMD in the form factor of a pair of eyeglasses. When used for vital sign monitoring, Google Glass has the potential benefit of improved comfort because of its size (13.3 cm×20.3 cm), mass (36 g), and wireless design. The display is positioned on the right side of the right eye. HMDs and smart glasses may also be used to monitor patient alarms from multiple patients in an ICU. For example, ICU nurses could wear smart glasses to display when the vital signs of one of his or her patients become abnormal. As can be seen in Figure 3, in addition to their inherent visual actuator, HMD or smart glasses can also feature tactile and auditory actuators. Audio can be transmitted to the user through bone conduction, and vibration sequences can be conveyed by placing a small tactor on the device. Therefore, designers have the option to combine these 2 additional interactive elements to enhance interaction with the clinician.

Figure 3. Interaction mechanism between the head-mounted display and the clinician. AS: actuator signal; EDS: external device signal; IS: interaction signal; PS: physiological signal; SS: sensory signal.



Augmenting Patient Monitoring With Smartwatches

Another wearable being explored by researchers for patient monitoring is the smartwatch, connected to the wireless network either directly or through the user’s smartphone or tablet. Most apps developed for smartwatches for health care monitoring

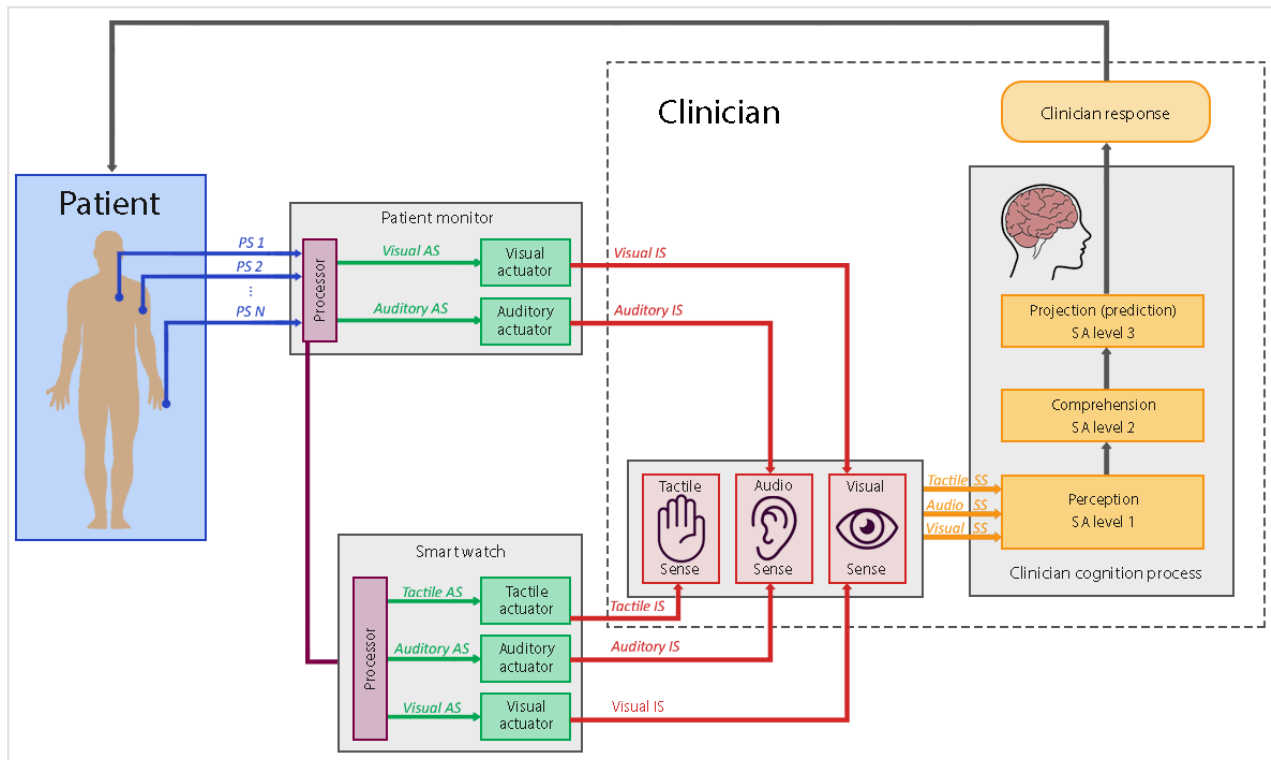
focus on its use as a sensor to monitor the wearer’s vital signs or health status [15]. However, given the increasing power of smartwatches, researchers are starting to investigate the feasibility of clinicians wearing smartwatches for patient vital sign or alarm display applications in critical care settings.

As shown in Figure 4, smartwatches can use 3 senses to convey information to the clinician.

Given the described challenges of monitoring critical care patients using PMs and the opportunities for wearable devices to address these challenges, the authors found it timely to investigate the state of the art in wearable devices applied to critical care patient monitoring. This study aims to critically

review the literature on wearable devices in critical care medicine in terms of design, performance, and usability and to explore how the participants in the different studies responded to the use of these wearable devices. This review critically analyzes the relevant literature, with a focus on the usability and human factors performance of the prototype devices reviewed.

Figure 4. Interaction mechanism between the smartphone/smartwatch and the clinician. AS: actuator signal; EDS: external device signal; IS: interaction signal; PS: physiological signal; SS: sensory signal.



Methods

Article Selection

A narrative synthesis approach was used in this scoping review. Although this is not a systematic review, the papers selected

for review were identified using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) [16]. The search by article title, abstract, and keywords was conducted in 4 relevant databases (Scopus, PubMed, Cochrane Library, and Engineering Village) using the keywords presented in Textbox 1.

Textbox 1. Keywords used in the database search. The keywords are grouped into 4 categories: keywords related to wearable devices, usability and human factors, hospital settings, and vital sign monitoring.

| |
|--|
| <p>Wearable devices (AND)</p> <ul style="list-style-type: none"> “wearable” OR “tactile” OR “head-mounted” OR “google glass” OR “smart glasses” OR “smartwatch” OR “smart watch” <p>Usability and human factors (AND)</p> <ul style="list-style-type: none"> “human factor*” OR “usability” OR “ergonomic*” OR “human error” OR “UX” OR “user experience” OR “situation* awareness” OR “response time” OR “detection time” OR “performance” OR “accuracy” OR “efficiency” OR “effectiveness” OR “satisfaction” <p>Hospital settings (AND)</p> <ul style="list-style-type: none"> “hospital” OR “intensive care” OR “ICU” OR “critical care” OR “operating room” OR “emergency department” OR “cardiology” OR “surgery” OR “anesthesia” <p>Vital signs monitoring</p> <ul style="list-style-type: none"> “vital sign” OR “heart rate” OR “spo2” OR “blood pressure” OR “respiratory rate” OR “h*modynamic” OR “alarm” OR “monitoring parameter” OR “physiologic*” |
|--|

The literature search included data up to May 2020, with no cutoff on the start date. Articles were further excluded after title, abstract, and full paper analysis by members of the multidisciplinary team (composed of engineers, health scientists, nurses, anesthesiologists, human factors specialists, and medical consultants). To ensure that all the relevant studies were identified, the team reviewed each paper's references, looking for possible studies that were not captured with our search strategy, and 1 study was identified [3].

Inclusion and Exclusion Criteria

The focus of the review is on the human factors and usability of prototype wearable devices from research laboratories designed to augment PMs to enhance patient monitoring and to overcome PMs' identified limitations in critical care medicine. On the basis of this focus, the inclusion criteria used in this review were as follows:

1. Studies must be published in English and appear in peer-reviewed academic sources.
2. The prototype display must be a wearable device designed for real-time physiological monitoring or feedback in critical care.
3. The study must include user testing of the prototype display and present the test findings.

Data Analysis

The data analysis involved carefully reviewing each paper to extract the following information and present it in a summarized form in the paper:

1. Display modality: for example, tactile, auditory, and visual
2. Intended user: for example, nurse, surgeon, and anesthesiologist
3. Intended use:
 - Single or multiple patient monitoring
 - Continuous vital sign monitoring or alarm condition alert

4. Study design adopted to evaluate the display:
 - The participant's clinical expertise
 - The environment in which the device was evaluated
 - Simulated or real clinical procedure used
 - Control device adopted
 - Outcome measures used
 - Usability and clinical performance evaluated
 - Within-subject or between-subject design

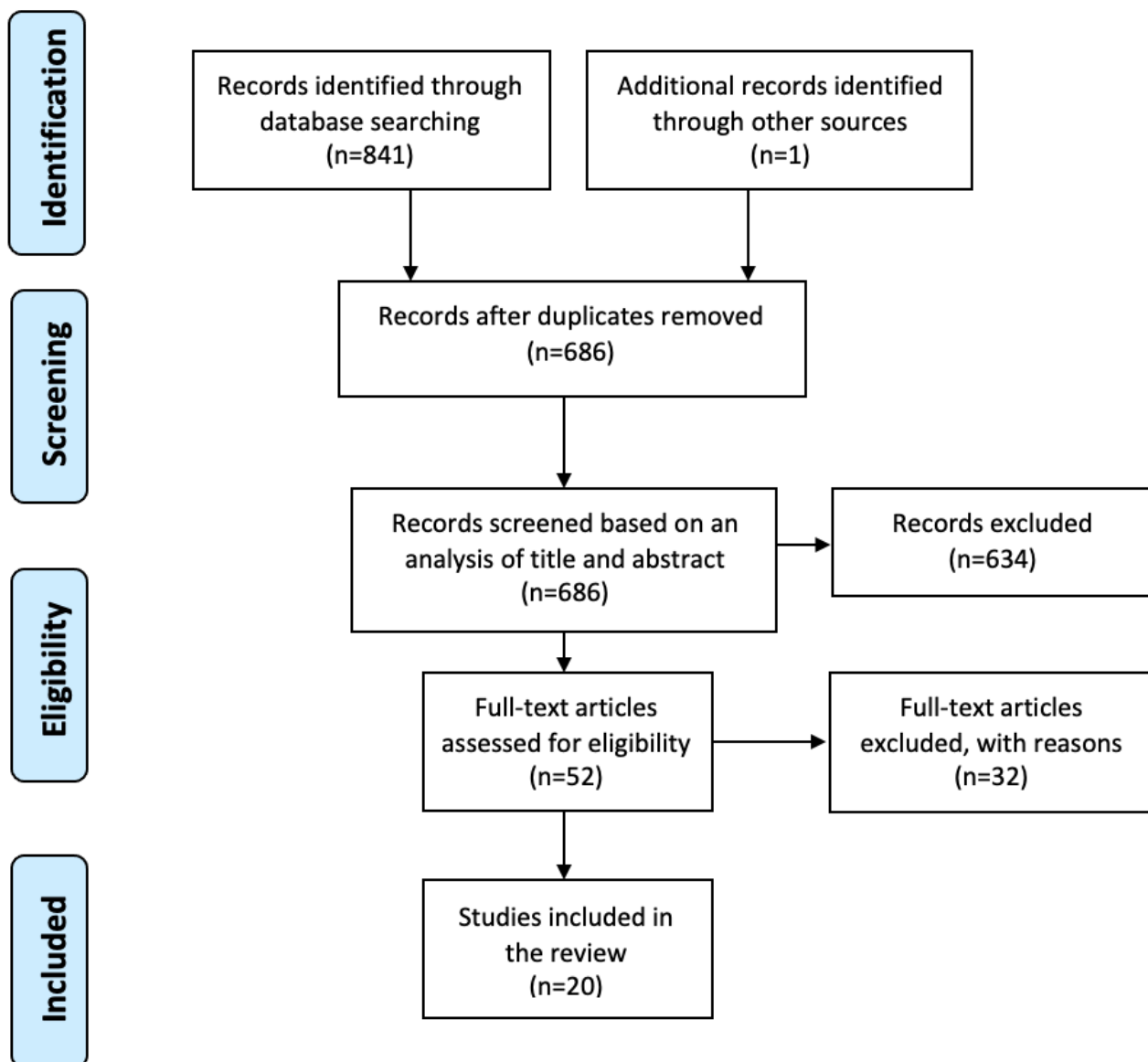
Results

Overview

A breakdown of the article search using the PRISMA guidelines can be seen in [Figure 5](#).

In the *identification* phase of the review, the search of the databases, using the chosen keywords described in [Textbox 1](#), provided a total of 841 records. In the *screening* phase, duplicate records were removed, resulting in 684 remaining records. These were reviewed by title and abstract. We identified that 634 studies clearly did not meet the inclusion criteria and were therefore discarded. In the *eligibility* phase, the full text of the remaining 52 studies was examined in more detail, and a further 32 studies were excluded for not meeting the inclusion criteria. The 20 remaining studies were *included* in this review. In reporting on these studies, a standardized method of reporting on the terminology and performance variables was created, as different studies used different names for the same parameters and other names for the same technology or techniques, which could create confusion for the reader. Therefore, a mapping between the new standardized naming convention and the other names was created and is presented in [Multimedia Appendix 1](#). The studies included were grouped into 3 categories, depending on the type of wearable device involved. A total of 10 studies investigated the use of *tactile displays*, 10 studies investigated the use of *HMD* or smart glasses, and 1 study investigated the use of *smartwatches*.

Figure 5. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines flow diagram depicting how many records were identified, screened, assessed, and included in the review.

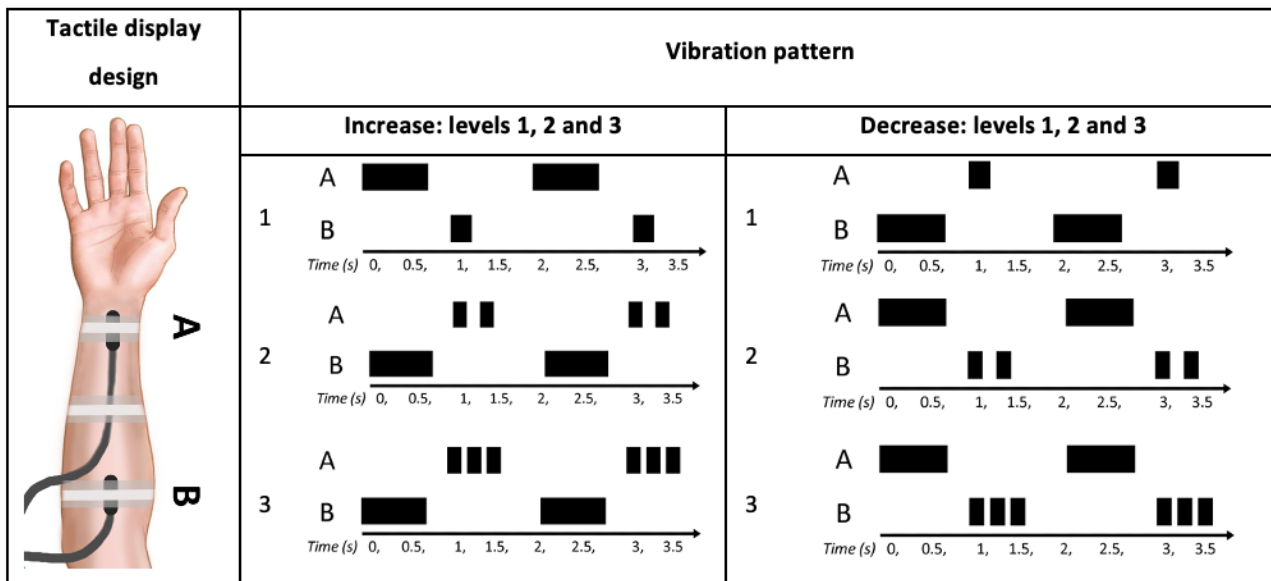


Tactile Displays

A total of 10 studies investigated the use of tactile displays as patient monitoring devices for critical care. The first investigation of tactile displays for anesthesia monitoring was conducted by Ng et al [17]. Ng et al [17] developed a tactile display prototype composed of 2 vibrating motors located on

the forearm (Figure 6). These vibration motors generated 6 different alarms, provided by 6 different vibration patterns, corresponding to a +10%, +20%, +30%, -10%, -20%, and -30% change in the variable of interest. The tactile display was compared with an auditory display, which provided 6 different alarms, provided by 6 different auditory patterns, depending on the variable change level and direction.

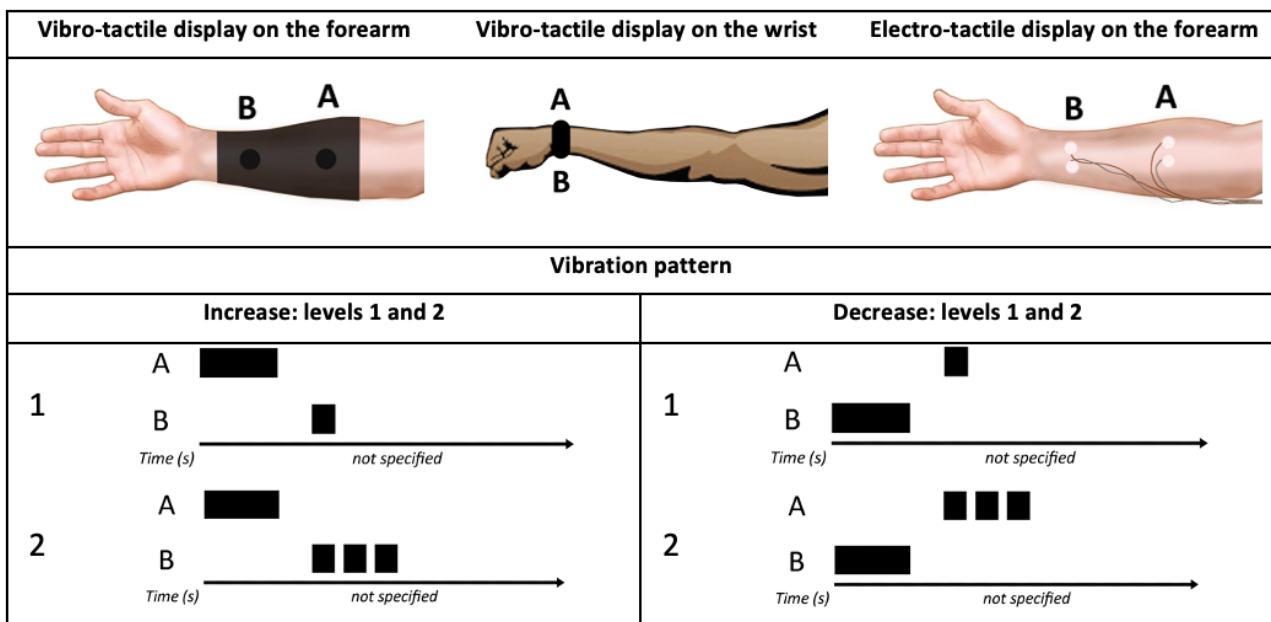
Figure 6. Tactile display on the forearm containing 2 factors (A and B). The prototype was intended to monitor a single variable with 6 distinct vibration patterns: 3 to represent different levels of increase and 3 to represent different levels of decrease in the monitored variable. The black-block pattern indicates the tactile at that location is activated at that point in time. Note that the increase and decrease patterns are the same except that the A and B sites are interchanged (a model of the concept presented in the paper).



A total of 10 engineering students with no anesthesia training were asked to test the tactile display, an auditory display, and a combination of these 2 displays. The interaction signal (IS) detection by the participants was statistically significantly better when using the tactile display or a combination of the tactile display and auditory display than when using the auditory display alone. Six participants commented on the auditory display's poor ability to attract attention, which explains the faster IS detection for the tactile display. On the other hand, regarding usability, 9 participants reported some discomfort with the wearables, citing arm numbness, resulting from the tightness of the elastic strips; itchiness caused by the vinyl sheet connecting the vibrating motors; and a restriction of arm motion from the nonwireless tactile prototype. Two years later, Ng et al [18] evaluated a new vibrotactile display on the forearm, a vibrotactile display on the wrist, and an electro-tactile display on the forearm. The vibrotactile display on the forearm and the vibrotactile display on the wrist used direct current motors to generate vibrations at the forearm (tactors), and the electro-tactile display on the forearm used a low voltage (9 V) nerve stimulator in the forearm skin to convey information

(Figure 7). The study aimed to identify which mechanism was more suitable for a tactile display (electro-tactile or vibrotactile) and the preferred location on the body for it to be located (wrist or forearm). It was found that the mechanical vibration was superior to the electrical stimulation in terms of learnability and IS identification. Participants (26 individuals with no medical training) experienced discomfort when using the electro-tactile display prototype and found it more challenging to identify patterns with this display; more than 80% of participants preferred the vibration instead of electrical stimulation. No significant differences were found between the 2 vibrotactile displays. Ng et al [17,18] introduced the concept of vibrotactile displays for patient monitoring and reported that vibrotactile displays were superior in terms of comfort to electro-tactile displays. All later studies involving tactile displays used vibration instead of electrical stimulation. However, it is important to note that, ultimately, novel devices should be tested by the intended end users (experienced anesthesiologists) rather than nonclinicians, as was the case with these studies.

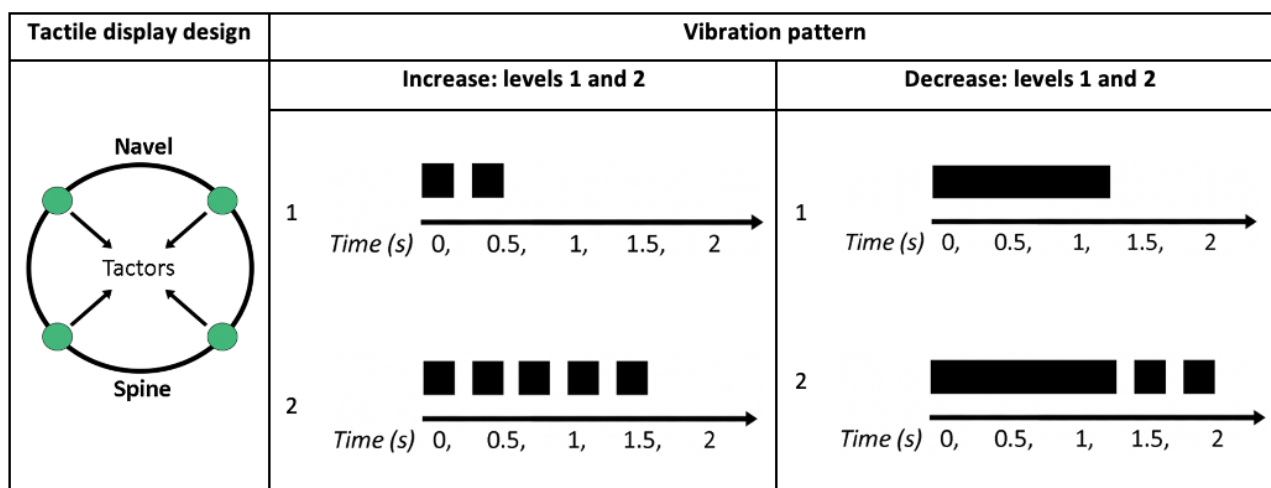
Figure 7. Three tactile displays monitoring a single variable using the same vibration/electrical stimulation pattern. The electro-tactile display on the forearm stimulated mechanoreceptors at 2 forearm locations (a model of the concept presented in the paper).



The display by Ng et al [19] worked in a similar manner to the previously discussed devices, but it was designed to be worn around the waist by anesthesiologists during an anesthesia procedure. It could monitor up to 4 variables simultaneously (Figure 8), with each factor capable of generating 4 different vibration patterns. Therefore, a total of 16 different vibration patterns could be decoded by the clinician with this display. A total of 15 participants (certified specialist anesthesiologists and anesthesia residents) were asked to wear the tactile belt prototype and identify the IS being conveyed. The authors found that the IS identification was approximately 97% in low

workload conditions and 93% in high workload conditions. The percentage of failed IS *detection* was 2% in low workload conditions and 17% in high workload conditions. Participants were reported to be satisfied with the user interface, but some participants expressed a preference for reducing the amount of information displayed. Although the study by Ng et al [19] demonstrated that potential end users could decode the information conveyed by the waist-worn tactile display, it is not possible to determine if these results indicate an improvement in patient monitoring, as this novel display was not tested against a PM.

Figure 8. Tactile display worn around the waist. Each factor represented a variable with 4 possible vibration patterns (permission to use the image obtained through RightsLink).



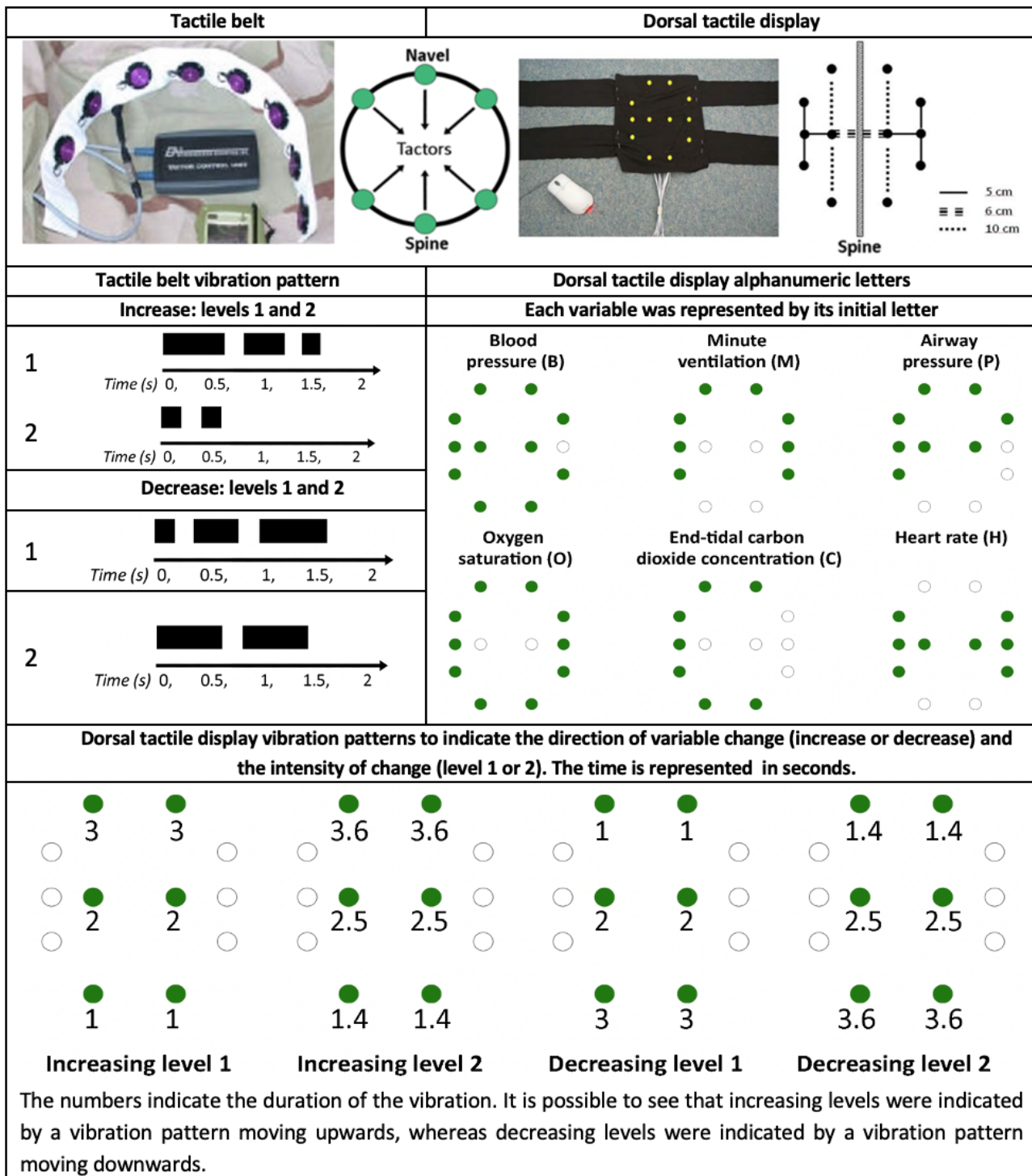
The tactile device presented in Figure 8 was tested again in 2012 by Dosani et al [20]. This time, the tactile display was used to monitor pediatric patients undergoing general anesthesia. A total of 17 anesthesiologists (with a minimum of 3 years of experience with patient care) were asked to wear the tactile belt during anesthesia procedures. Once the patient’s physiological state was considered stable by the anesthesiologist, he or she

turned on the tactile display, which then started receiving real-time vital sign data wirelessly from the PM. Every time that the belt vibrated, the anesthesiologist echoed their understanding of the tactile message into a computer. The device was evaluated in terms of *IS detection*, *IS identification*, and user *satisfaction*. In total, 530 alerts were delivered during the study, with 81.0% of them being decoded by the

anesthesiologists (*IS detection*), and participants accurately identified 89.5% of the alerts (*IS identification*). In the study by Ng et al [19], as there was no control group in this study, it was not possible to determine if improved patient monitoring occurred. However, by testing this novel display with the desired end users during real patient monitoring, the authors acquired valuable usability information. Most participants indicated that they were comfortable wearing the tactile belt, whereas 6 participants reported that they would not be able to wear the tactile belt for a full workday. Clinicians reported that the mental process of decoding of messages became easier, with less mental effort, the longer the device was used, highlighting the importance of extended exposure to devices before testing. Barralon et al [21] compared 2 tactile display prototypes: a tactile belt to be used around the waist and a dorsal tactile display with an array of tactors located along the spine (Figure 9). The tactile belt and dorsal tactile display could monitor 6 physiological variables. Each tactile represented a specific variable with 4 possible alerts to represent the direction of

change of the variable (increasing or decreasing), and the magnitude of change in the variable was categorized as level 1 or level 2. This resulted in 24 different alerts ($6 \times 2 \times 2$) that could be conveyed using the devices. Using 28 participants with no medical background, it was found that dorsal tactile display was easier to learn than tactile belt. It took longer to display the message with dorsal tactile display alerts (mean of 4.3 seconds) than with tactile belt alerts (mean 1.3 seconds). Participants using the tactile belt had a shorter *response time* than those using the dorsal tactile display. When measured from the end of the IS, however, the *response time* was shorter when participants used dorsal tactile display than that when they used tactile belt. This reflects the impact of the IS duration on *response time*. However, no statistically significant difference was found regarding *IS identification* of both devices. As these novel displays were not compared against a PM with clinicians, further studies to assess the usability of tactile belt and dorsal tactile display in clinical settings with the intended users would be desirable.

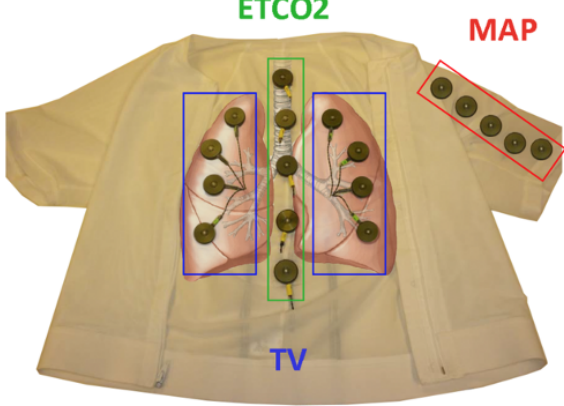


Figure 9. Tactile displays by Barralon et al [21]. Tactile belt worn around waist and dorsal tactile display positioned along the back. The tactile belt was designed to monitor 6 variables, each represented by a factor with 4 possible vibration patterns. For the dorsal tactile display, each variable was represented by the factors forming its initial letter. For each letter, the sequential locations were activated for 300 milliseconds, followed by a 700-millisecond pause and a sequence of vibrations to indicate the level and direction of change (permission to use the image obtained through RightsLink).



Ferris and Sarter [22] developed a tactile display to monitor 3 variables. As shown in Figure 10, the apparatus had 3 different display modes: *alarm display*, *continuous display*, and *hybrid display*. The alarm display worked in a similar manner to the tactile displays previously discussed. The continuous and hybrid

displays were 2 new concepts for tactile displays, which had not been tested before. The differences between these 3 display modes are detailed in Figure 10 (image created based on the concepts presented in the paper and in Ferris' PhD dissertation [23]).

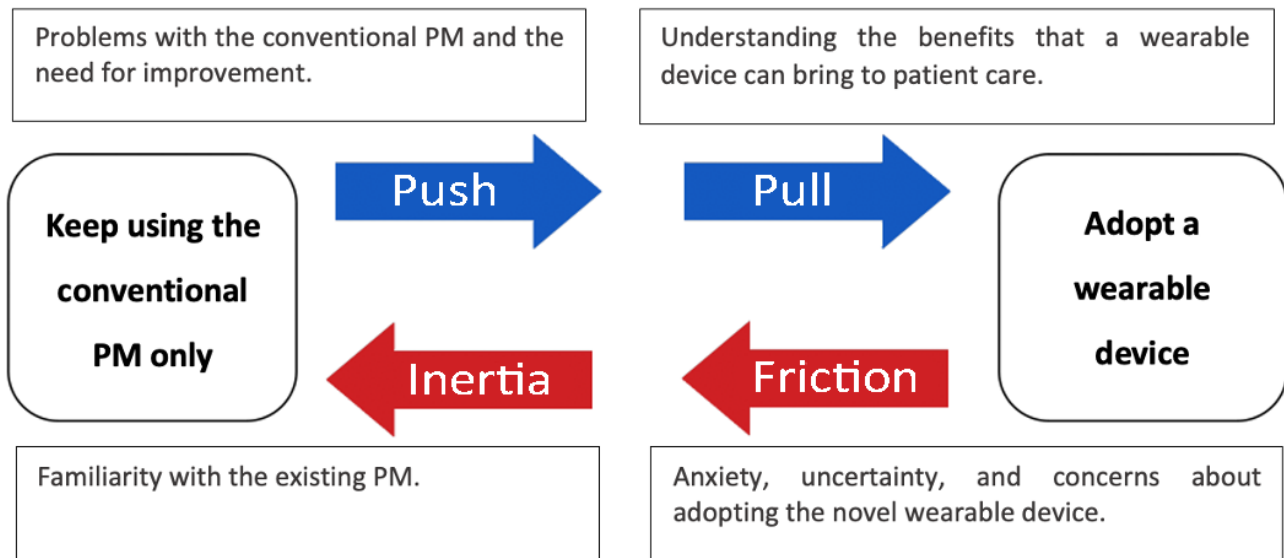
Figure 10. Tactile display by Ferris and Sarter [22]. The vest could be configured in 3 different modes: alarm, continuous, and hybrid display (image created based on the concepts presented in the paper and Ferris' PhD dissertation).

| Tactile display design | Vibration pattern for the alarm display |
|--|--|
|  <p>Tactors mapped to the physical location of corresponding variable for ETCO₂ (chest) TV (spine). MAP tactors were placed along the left upper arm.</p> | <p>As an alarm display, the tactile display presented vibrations at the appropriate location when a variable exceeded the acceptable range, and the vibration pattern was used to indicate whether the low or high threshold value had been exceeded. The tactors vibrated according to the following pattern.</p> <div style="text-align: center;">  <p>Time (s) 0, 0.5, 1</p> </div> <p>When the upper/lower threshold was exceeded, the top/bottom tactor vibrated.</p> |
| Vibration pattern for the continuous display and Hybrid display | |
| <p>As a continuous display, it continually informed user on current levels of 3 variables using natural mapping. During “normal” conditions for the MAP and ETCO₂, the tactors at the center would vibrate every 3 seconds using the pattern.</p> <div style="text-align: center;">  <p>Time (s) 0, 0.5, 1</p> </div> <p>When either of 2 variables became abnormal (increased or decreased level 1), the vibration would occur immediately above or below the center tactor. When the abnormality reached level 2, the vibration would occur on the top or bottom tactors of these axes. The intensity of the vibration would also change according to its values.</p> | <p>For TV, vibrations began at the bottom tactors for each lung and continued upward to the other tactors, representing “filling” of the 2 lungs. As the fill pattern traveled upward, vibrations increased in intensity to represent sensation of pressure. Duration of the vibration pattern varied according to the patient’s respiratory rate.</p> <p>The hybrid display followed the same presentation rules as the continuous display, with some adjustments to incorporate characteristics of the alarm display. For example, whenever variable levels became abnormal, the characteristic vibration pattern for that variable was replaced with the vibration pattern from the alarm display.</p> |

In this study, 16 anesthesiologists were asked to (1) complete each scenario (containing at least 50 tasks each) as quickly as possible and (2) maintain the monitored variables within acceptable levels. The authors found that the *event detection time*, *event correction time*, and *multitasking performance* were statistically significantly improved when using the tactile displays compared with the PM. For instance, the mean event detection time was 56.4 seconds with the PM, 28.1 seconds with the alarm display, 26.8 seconds with the continuous display, and only 14 seconds with the hybrid display. No statistically significant differences were found for task completion time between displays. Despite the hybrid display’s better performance, participants felt that the alarm display and the PM

display supported multitasking performance better. The authors suggest that this may be because of the display’s novelty and that participants would be inclined to choose interfaces they were familiar with over new ones. In addition, the participants considered the continuous and hybrid display uncomfortable, which can invariably generate concerns. These factors are all part of the balance of forces acting on the clinicians when deciding if they should augment the PM with a wearable display for critical care monitoring or continue using a PM only. This concept is presented in a diagram (Figure 11) adapted from “The Science of How Customers Buy Anything” by Murya [24].

Figure 11. Balance of forces acting on the decision making of the clinicians when deciding if they should augment the patient monitor (PM) with a wearable display for critical care or continue only using the PM. Diagram adapted from the concept presented in “The Science of How Customers Buy Anything,” by Maurya [24].



This feedback reinforces the importance of incorporating more extended familiarization with the wearable display before testing (especially when the wearable display has a large number of new concepts to be learned) and making the wearable as comfortable as possible.

McLanders et al [25] investigated the use of tactile displays to continuously convey information from a pulse oximeter. In the study by McLanders et al [25], HR was continuously displayed as *very high, high, normal, low, or very low*, and the SpO₂ was displayed as *normal, low, or very low*. As in the study by Ferris

and Sarter [22], this reflected an attempt to communicate absolute values for the variables instead of communicating alarms only. As hospitals in the United Kingdom and Australia have adopted a *bare below the elbows* infection control policy since 2011, the authors determined that it was inappropriate to wear the tactile on the forearm and placed it on the upper arm instead. As shown in Figure 12, the tactile display could be used in 2 modes: *separated* and *integrated*. In the *separated* display, the HR alert was displayed first, followed by the SpO₂ alert. In the *integrated* display, both variables were displayed using a single alert.

Figure 12. An elasticized tactile display sleeve on the upper arm with 3 tactors (A, B, and C) monitoring heart rate (HR) and saturation of peripheral oxygen (SpO₂). This display could be used in 2 display modes: separate and integrated. In the separated display, the HR signal came first, followed by the SpO₂ alert. In the integrated display, both alerts were displayed with a single alert (a model of the concept presented in the paper). H: heart rate; H: high; L: low; N: normal; VH: very high; VL: very low.

| Tactile display design | Vibration pattern for HR and SpO ₂ separately | | Vibration pattern for HR and SpO ₂ integrated | | | |
|------------------------|--|--|--|--|--|--|
| | HR | SpO ₂ | HR | Normal | Low | Very low |
| | Very high | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | Very high | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified |
| | High | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | High | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified |
| | Normal | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | Normal | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified |
| | Low | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | Low | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified |
| | Very low | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | Very low | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified | A [vibration bar] B [vibration bar] C [vibration bar] Time not specified |

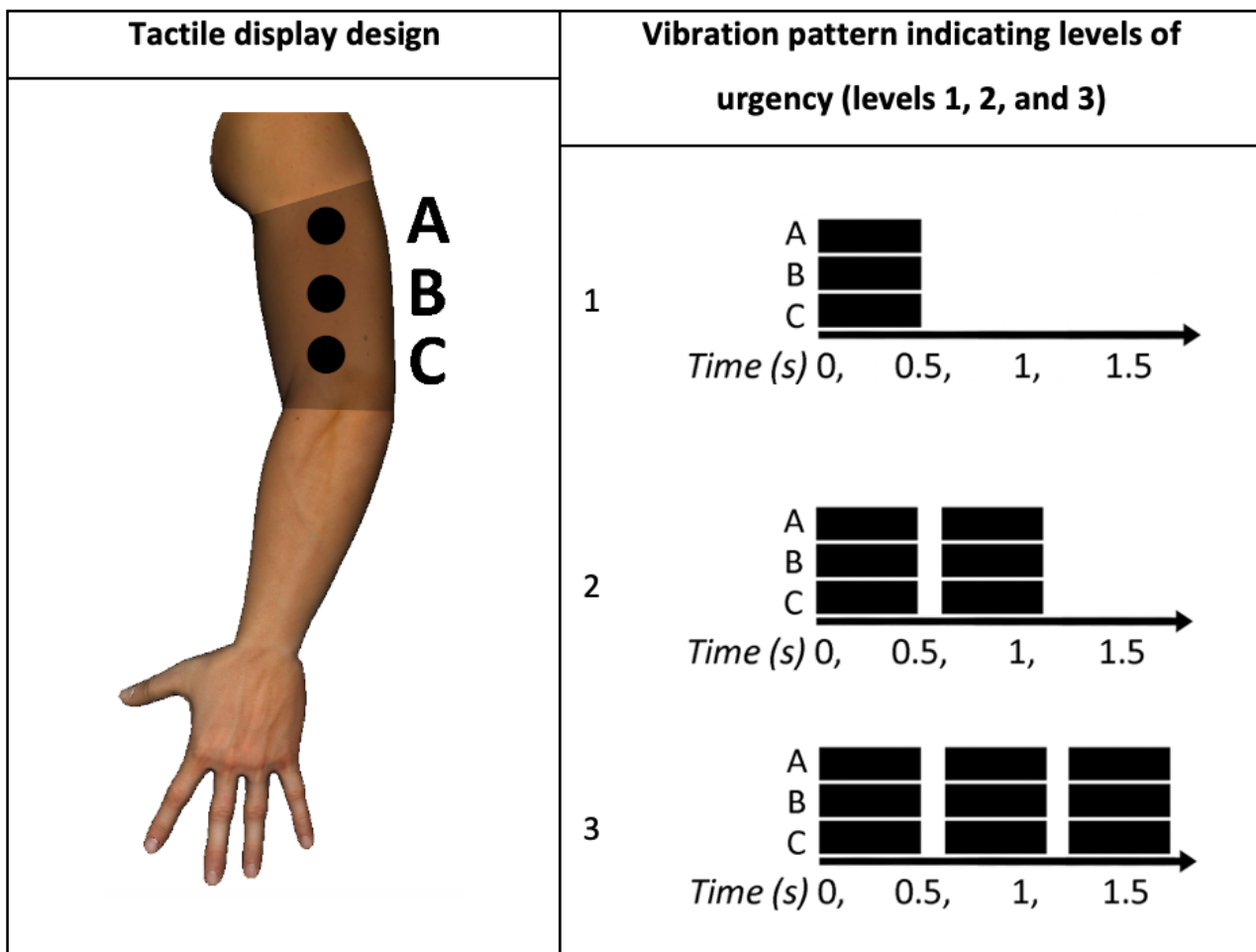
In a between-subjects study, 30 participants with no medical background were asked to test the prototype and to identify 5 ranges of HR and 3 levels of SpO₂ in random sequences generated by a computer. Results showed no significant differences regarding *alert identification*, with participants recognizing over 90% of the changes in HR and SpO₂ in both modes. There was a significant effect of display mode on the response time, with participants responding faster in the integrated mode. Regarding comfort, participants were moderately positive, with a mean score of 6.8 out of 9 on the comfort scale. The authors suggest that the use of wireless factors may have contributed to the comfort of the devices, as they require less adhesive tape to secure the tactile display in place.

Cobus and Heuten [26] developed and tested a tactile display with the ICU nurse as the intended user. Unlike previous studies, the prototype used by Cobus and Heuten [26] was designed as an alarm system to inform the nurse of a possible risk to the patient, irrespective of which vital sign triggered the alarm, and was intended to reduce auditory alarm fatigue for nurses and patients by displaying the alarms silently. For this reason, only

3 vibration patterns were required to indicate 3 levels of urgency (eg, low, medium, and high). Similar to the study by McLanders et al [25], the display was placed in the upper arm for hygienic and safety reasons.

The prototype was tested initially by 12 participants with no medical background and then by 12 nurses to determine which alerts were better in terms of usability and comfort. The alert set shown in Figure 13 was chosen as most appropriate because of better IS identification. Although the chosen pattern was chosen as being most appropriate, it is worth noting that it may not be ideal for other tactile displays depending on the number of variables monitored, the tactile display position, and the context of use. Participants were also asked to complete a system usability scale (SUS) questionnaire to evaluate usability and a comfort rating scale (CRS) to evaluate the comfort of the prototype. The mean SUS was 95 (out of 100, which indicates very good usability), and a positive result for the CRS was also found. However, some participants reported that the device imposed arm movement limitations, revealing the importance of requiring the completion of physical tasks when testing these types of devices.

Figure 13. An elasticized sleeve on the upper arm holding 3 factors (A, B, and C). Three vibration patterns indicated 3 levels of urgency, with the pattern repeating itself after a 800 milliseconds pause (a model of the concept presented in the paper by Cobus and Heuten [26]).



Burdick et al [27] investigated the effect of a multisensory alarm system that combined an auditory display with a tactile display. The multisensory display was compared with a unisensory display (auditory display only) regarding *alert identification*

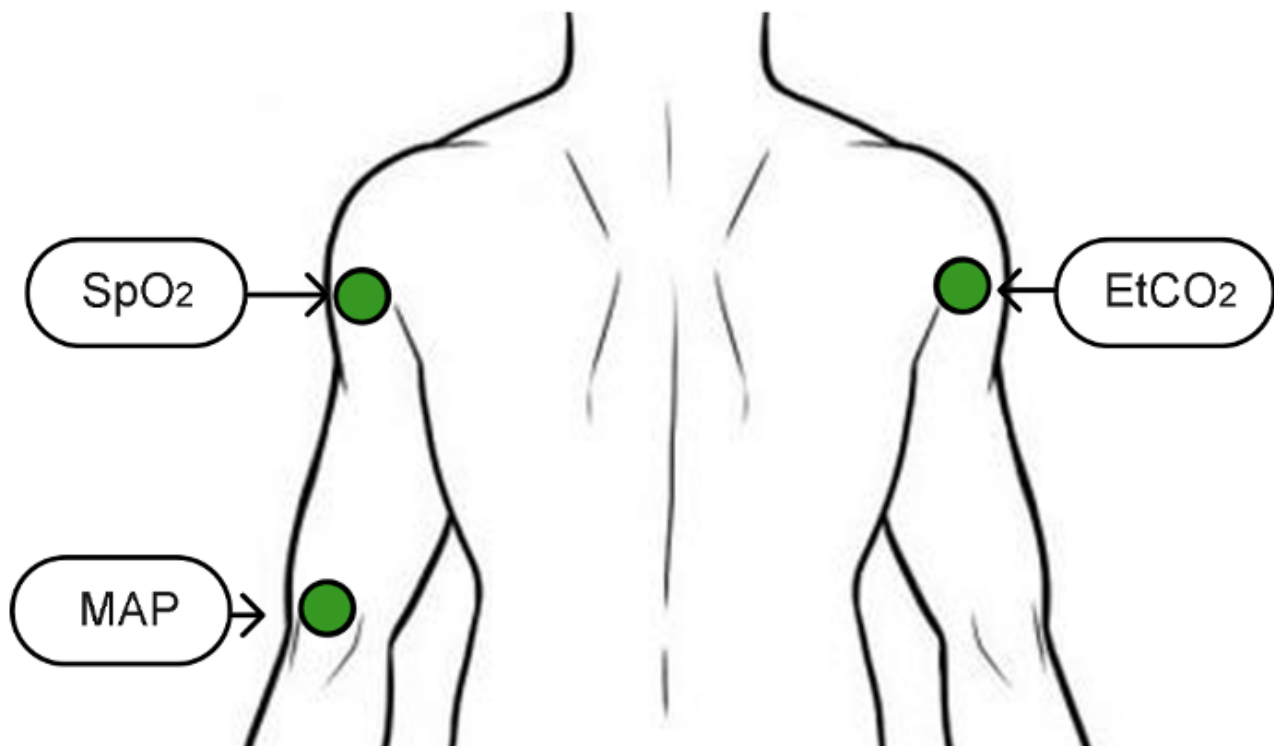
(identification of the variable, point of change, and direction of change). Interestingly, the auditory display used musical instruments to represent the variables: HR (drums), BP (piano), and blood oxygenation (guitar). Each variable had 3 levels of

decrease, a normal level, and 3 levels of increase. The different levels were represented by changes in the timbre of the respective instrument. In the multisensory display, the different levels were also represented by a tactile display, where the auditory information was translated into vibration with equal rhythm and amplitude. Testing with nonmedical participants revealed that participants were better able to identify alerts when using the multisensory display. The authors commented that multisensory display might relieve auditory alarm fatigue in critical care.

The tactile display studies discussed varied significantly in design (eg, variables monitored, location of the display, and vibration pattern). This reveals a lack of consensus on the best tactile display design for critical care medicine. Gomes et al [14] aimed to address this literature gap by conducting 2 experiments. In the first one, the authors evaluated the usability of the 3 main parameters of tactile displays: intensity of

vibration, vibration pattern, and position of factors. In total, 22 health care professionals were asked to test a tactile display, similar to the one described in Figure 13, and answer a set of usability questions about the alerts presented. On the basis of the results of the first experiment, Gomes et al [14] then designed the tactile display presented in Figure 14. Like Ferris and Sarter [22], Gomes et al [14] understood that the use of mapping can be an effective way to improve the device's usability. However, instead of mapping the location of the factors to the physical body location of the corresponding variable, the factors were mapped to the display locations in a PM. For instance, SpO₂ and mean arterial BP values were displayed on the left side of the PM used by the participants, with SpO₂ located above mean arterial BP, whereas end-tidal carbon dioxide partial pressure (EtCO₂) was shown on the right side.

Figure 14. Tactile display, 3 types of alerts used for each variable: increasing, decreasing, and normalizing using 8 consecutive vibrations (500 milliseconds in duration). If the variable value was increasing, the intensity of the vibration increased during the 8 consecutive vibrations, and if the variable value was decreasing, the intensity of the vibration decreased. When the variable value was normalizing, the intensity was kept constant (a model of the concept presented in the paper by Gomes et al [14]). EtCO₂: end-tidal carbon dioxide partial pressure; MAP: mean arterial blood pressure; SpO₂: oxygen saturation.



A total of 19 participants (9 attendings, 7 residents, and 3 certified registered nurse anesthetists) tested the developed tactile display and identified the presented cues with a response accuracy of $\geq 90\%$.

A summary of the results of the studies involving tactile displays is presented in Appendix 2 [14,17-22,25-35]. It should be noted that it is sometimes difficult to compare the same metrics across different studies, as study design differences can make comparison meaningless. Most tactile displays reviewed were prototype devices developed to determine the feasibility of using the tactile sense to convey the patient's physiological state. For this reason, most authors focused on the subject's capability to

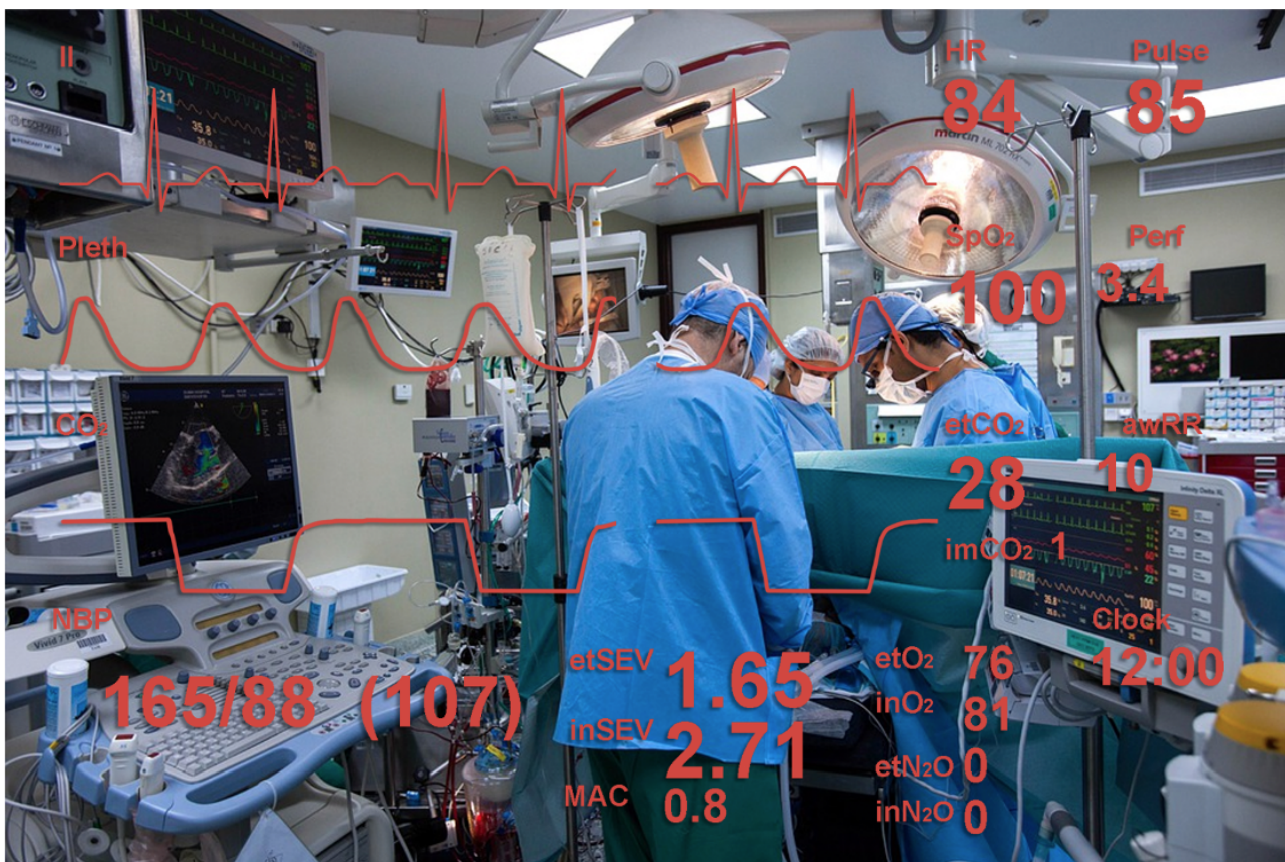
detect, identify, and respond to an IS produced by the tactile display. Therefore, the performance metrics most evaluated in the studies involving tactile displays were *IS detection*; *IS identification*; *response time*; and some usability metrics such as *comfort*, *satisfaction*, and *general usability*. These metrics were chosen as they were used by most studies reviewed. For the purpose of uniformity, the values of usability metrics that were evaluated using scales (eg, SUS, Likert-type scales) were converted to a scale of 1 to 7, with 1 being very negative and 7 being very positive (eg, a 3 in a 1-5 scale became a 4 in this 1-7 scale).

Head-Mounted Displays

Sanderson et al [28] evaluated the advantages and disadvantages of HMD for anesthesiologists compared with traditional auditory displays. They asked 16 participants (7 consultants and 9 residents) to supervise the activities of a resident (an actor) during anesthesia under 4 display conditions: *visual* (PM plus variable-tone pulse oximetry [control condition]), *HMD* (*visual* plus HMD), *audio* (*visual* plus respiratory sonification and BP audio IS) and *both* (*HMD* plus *audio* conditions). The HMD

presented the vital signs in a manner similar to that shown in Figure 15, but without the traces. Significantly more events were detected with *audio* and *both* conditions compared with the *visual* condition only. However, no statistically significant differences were found when comparing HMD and visual conditions. No differences were found regarding the *event detection time* for all displays. When asked about their preferences, most participants (83%) liked the easy availability of information on the HMD, but 56% disliked comfort aspects such as weight and size and referred to experiencing headaches.

Figure 15. A visual representation of the view of an anesthesiologist wearing the head-mounted displays presented in Liu et al [29]. awRR: airway respiratory rate; CO₂: carbon dioxide; EtCO₂: end-tidal carbon dioxide partial pressure; etN₂O: end-tidal nitrous oxide concentration; etSEV: end-tidal sevoflurane concentration; HR: heart rate; imCO₂: inspired minimum CO₂; inN₂O: inspired nitrous oxide concentration; inSEV: inspired sevoflurane concentration; MAC: minimum alveolar concentration; NBP: noninvasive blood pressure; SpO₂: oxygen saturation.



Liu et al [29] investigated if HMD during anesthesia procedures would worsen *inattentive blindness*, for example, the HMD may put the anesthesiologist in a state of immersion resulting in him or her missing salient, unexpected events that they would otherwise not miss. This issue has been reported in other domains such as aviation [36]. In the study by Liu et al [29], the variables were displayed in the same format as in the PM, with the waveforms presented on the left and digital numeric values on the right. However, all the variables were displayed in red instead of a color-coded format frequently used in PMs (Figure 15). Two experiments were conducted with an HMD connected to a PM. In the first experiment, 12 anesthesiologists were asked to perform surgical simulation scenarios in 3 different contexts: focal depth of the HMD near, focal depth of the HMD far, and no HMD. It was found that *event detection* and *event detection time* were not significantly affected by the use of HMD (near or far focus), suggesting that *inattentive*

blindness may not be a major cause of concern. Importantly, it was found that participants spent more time looking toward the patient rather than the monitor when using the HMD (near or far focus). In general, participants found the non-HMD the easiest and preferred condition. Participants liked that the HMD gave them the capability to monitor the patient's vital signs, irrespective of the direction of their gaze or their location in the operating room. Nonetheless, they disliked the weight or size of the HMD and associated computer equipment and the difficulty of focusing on the HMD, which caused eye fatigue. Participants also preferred the near-focus setting when using the HMD.

In the second experiment conducted by Liu et al [29], the goal was to examine whether or not HMDs would be useful if anesthesiologists were operationally and physically constrained (PM behind them, forcing participants to rotate their trunks to observe PM). Under these circumstances, participants using the

HMD significantly improved *event detection time* in 2 of the 3 scenarios (light anesthesia and hypovolemia). However, in the excess sedation scenario, *event detection time* was significantly lower. Once again, participants spent more time looking at the patient rather than at the monitor when using the HMD during this experiment. Participants rated the scenarios in which they used the HMD, as being less busy, easier for monitoring patients, and faster for detecting vital sign changes than those scenarios with the PM only. Once again, participants liked not having to turn around to look at the PM but felt somewhat uncomfortable using the HMD because of the weight and size of the device and its associated equipment. The investigation conducted by Liu et al [29] revealed that, by reducing the number of required neck rotations by the anesthesiologist, HMDs had ergonomic benefits. In addition, by keeping the patient in his or her visual field for longer, the anesthesiologist is potentially less likely to miss a critical clinical event (eg, increase in skin pallor). Therefore, HMDs could not just increase comfort but also improve patient safety. In a 2010 paper, Liu et al [30]

investigated if using HMD during an anesthesia procedure would result in 6 anesthesiologists spending more time looking at the patient and less time looking at the monitor when delivering anesthesia to 6 real patients, alternating between the experimental condition (PM plus HMD) and control condition (PM plus HMD equipment without the monacle that displayed the vital signs). In the experimental condition, participants spent less time looking toward the workstation and more time looking toward the patient and the surgical field. Regarding comfort and satisfaction, although participants did not have significant positive or negative views about the HMD, they raised the same issues regarding the weight and bulk of the HMD, as in the study by Liu et al [29].

Three researchers evaluated the usability of Google Glass for patient monitoring. Drake-Brockman et al [37] evaluated the acceptance of Google Glass by 40 anesthesiologists in a pediatric anesthesia context. As shown in Figure 16, the interface design was composed only of the digital values for 4 variables: SpO₂, HR, BP, and ETCO₂.

Figure 16. A mock-up of the views experienced by anesthetists in the study by Drake-Brockman et al [37] (a model of the concept presented in the paper). EtCO₂: end-tidal carbon dioxide partial pressure; HR: heart rate; mBP: mean blood pressure; SpO₂: oxygen saturation.



An important finding was that the HMD comfort issues identified by Liu et al [29] were rectified with Google Glass. Participants reported that the device was comfortable to wear (90%), easy to read (86%), and not distracting (82.5%). Moreover, 76% of participants reported that they would use it again, and 58% indicated that they would recommend the device to a colleague. Anesthetists with less experience (generally

younger) were less averse to wearing the device in front of patients (78%) than more experienced ones (43%).

Liebert et al [31] also used Google Glass to display patient vital signs during a medical procedure. In the display used in the study by Liebert et al [31], the entire PM screen was visible in the top-right corner of the glasses (Figure 17) instead of only a subsection, as in the study by Brockman et al [37]. In total, 14

surgical residents participated in 2 simulated scenarios: a thoracostomy tube placement and a bronchoscopy, interacting with a high-fidelity mannequin (Laerdal SimMan 3G). Participants in the experimental group (1) recognized the event

(hypotension) faster, (2) made significantly fewer glances toward the PM, and (3) spent significantly less time looking at the PM. Similar results were found in the bronchoscopy scenario.

Figure 17. Representation of participant's view when wearing the Google glasses (a model of the concept presented in the paper by Liebert et al [31]).

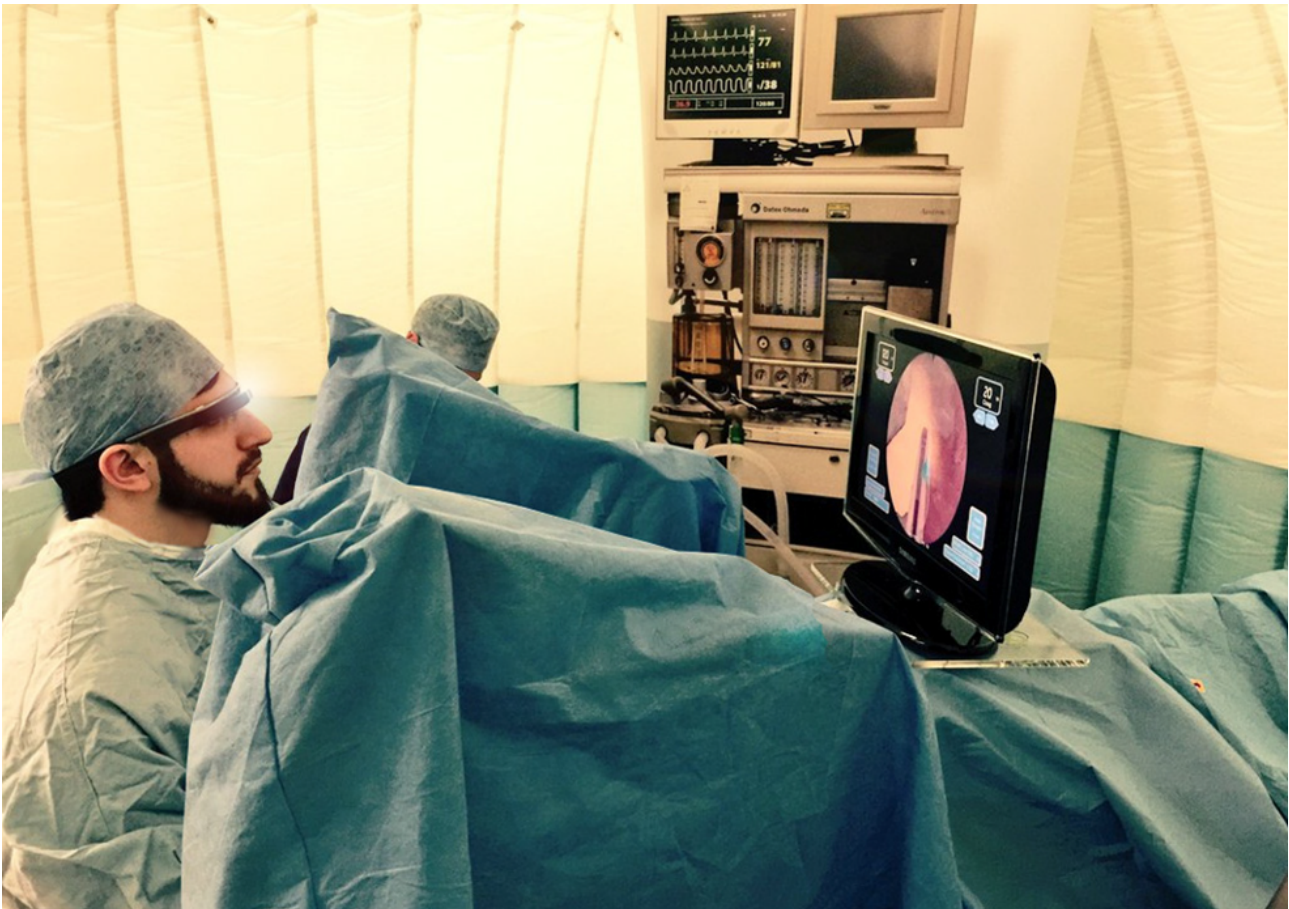


Most participants agreed that the device was easy to use (93%), improved their *situation awareness* (SA; 64%), helped to monitor vital signs (86%), and had the potential to improve patient care (85%). In addition, 86% of participants would consider using Google Glass in their future clinical practice.

Iqbal et al [32] evaluated the acceptance and performance of Google Glass with urologists. The interface designed for the experiment and the variables presented in the display were not provided. They asked 37 subjects (24 medical students, 8 urology surgical trainees, and 5 consultant urologists) to perform a simulated surgery (laser prostatectomy), initially using only the PM and then using the PM in conjunction with Google Glass. *Response time* to the vital sign changes was significantly shorter

when using the Google Glass (mean of 35.5 seconds) compared with PM only (51.5 seconds). There may have been an order effect, as all participants performed the control simulation first, followed by the experimental simulation using the same scenario. Most participants reported that Google Glass increased their awareness of vital signs and that they would use the device during surgical procedures. Participants who already wore prescription glasses and were left-handed reported discomfort wearing the device, as it needs to be placed on top of the user's glasses and only displays data to the right eye. The authors identified battery life and comfort issues for prescription glass users as potential barriers to its adoption into clinical practice. Figure 18 shows one of the study participants wearing Google Glass during a "GreenLight" simulated prostatectomy.

Figure 18. An urologist wearing Google Glass during a GreenLight prostatectomy. The patient monitor is visible in the top of the figure. During prostatectomy surgery, monitoring of patient's vital signs is primarily the responsibility of the anesthesiologist; however, Iqbal et al [32] argued that Google Glass enabled the urologist to focus on the surgical site without having to discuss vital signs with the anesthesiologist (permission to use the image obtained through RightsLink).



Schlosser et al [33] proposed the use of HMDs by anesthesiologists for vital sign monitoring of multiple patients simultaneously in operating rooms. Schlosser et al [33] used the Vuzix M300 (Vuzix Corporation) glasses and developed the user interface through a user-centered design process. The prototype (Figure 19) was connected to the PM network and could display a subset of the PM vital sign data for up to 6 patients and reproduce the alarm sounds for the different patients. A total of 8 anesthesiologists were asked to monitor 6 patients simultaneously for 3 hours while wearing the HMD and for 3 hours without the HMD. Schlosser et al [33] reported that the number of alarms detected by the anesthesiologists was significantly higher when using the HMD (66.7% vs 7.1%). This is a very significant result. With regard to the usability of the HMD, participants indicated satisfaction in terms of readability, interface structure, and navigation. However, they reported that the HMD interfered with the tie-on laces of the

surgical mask. In addition, 4 of the 8 participants considered the HMD too heavy (55 g) and too big. Another important issue raised was that participants considered the HMD alarms distracting when they were performing activities that required focus.

Cobus and Heuten [26], in addition to the upper arm tactile display presented in the previous section, designed an innovative way to silently alert ICU nurses of PM (silenced) alarms. The prototype wearable, presented in Figure 20, uses peripheral lights of 3 different colors to indicate a technical, low-priority, or high-priority alarm. Other wearable displays to present silenced PM alarms were also investigated: a wearable *audible* display that transmitted the PM alarms via bone conduction speakers using the same sounds used by the PMs and a *tactile* display that vibrated when an alarm occurred. Figure 21 depicts the light, vibration, and sound patterns generated by the different elements of the wearable.

Figure 19. Schlosser et al's [33] display, as presented in the head-mounted displays (HMDs) prototype. (A) alarms are displayed on the left side of the screen, and the digital values for heart rate, blood pressure, and saturation of peripheral oxygen are displayed on the right side. (B) A second screen of Schlosser's display was designed to present more details (such as a snapshot of the electrocardiogram curve) for one specific patient. In addition to the visual alarms, auditory alarms were displayed on the HMDs via bone conduction. To interact with the device, a button on the HMDs had to be pressed to cycle through the patients. (Permission to use the image obtained through RightsLink.) ABP: arterial blood pressure; HF: heart rate; NBP: noninvasive blood pressure; OP: operating room; SpO₂: oxygen saturation.

(a)

| | | | | |
|-------|--------------|--------|----------------|----------|
| OP 1 | ABPs 75 < 80 | HF 62 | ABP 75/46(63) | SPO2 100 |
| OP 2 | | HF 67 | ABP 98/55(71) | SPO2 100 |
| OP 3 | | HF 114 | NBP 98/44(51) | SPO2 100 |
| OP 4 | | HF 49 | NBP 113/80(92) | SPO2 97 |
| OP 13 | | HF 96 | NBP 112/67(88) | SPO2 99 |
| OP 14 | | HF 58 | ABP 97/85(89) | SPO2 100 |

(b)

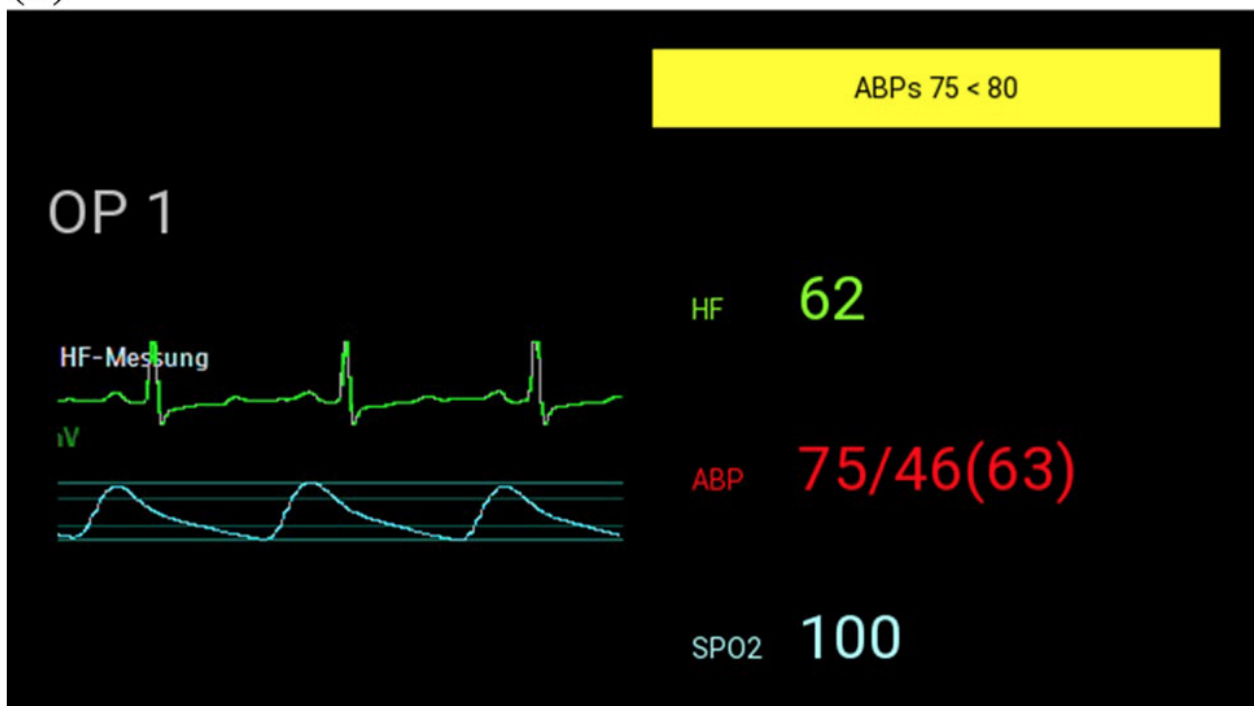


Figure 20. Cobus and Heuten’s [26] head-mounted displays displaying a high-priority alarm. All light-emitting diodes (LEDs) were activated simultaneously for the alarms. The peripheral light followed the alarm colors commonly used by patient monitors. Red was used for high-priority alarms, yellow for low-priority alarms, and blue for technical alarms (alarm indicating a technical problem, eg, sensor not connected).

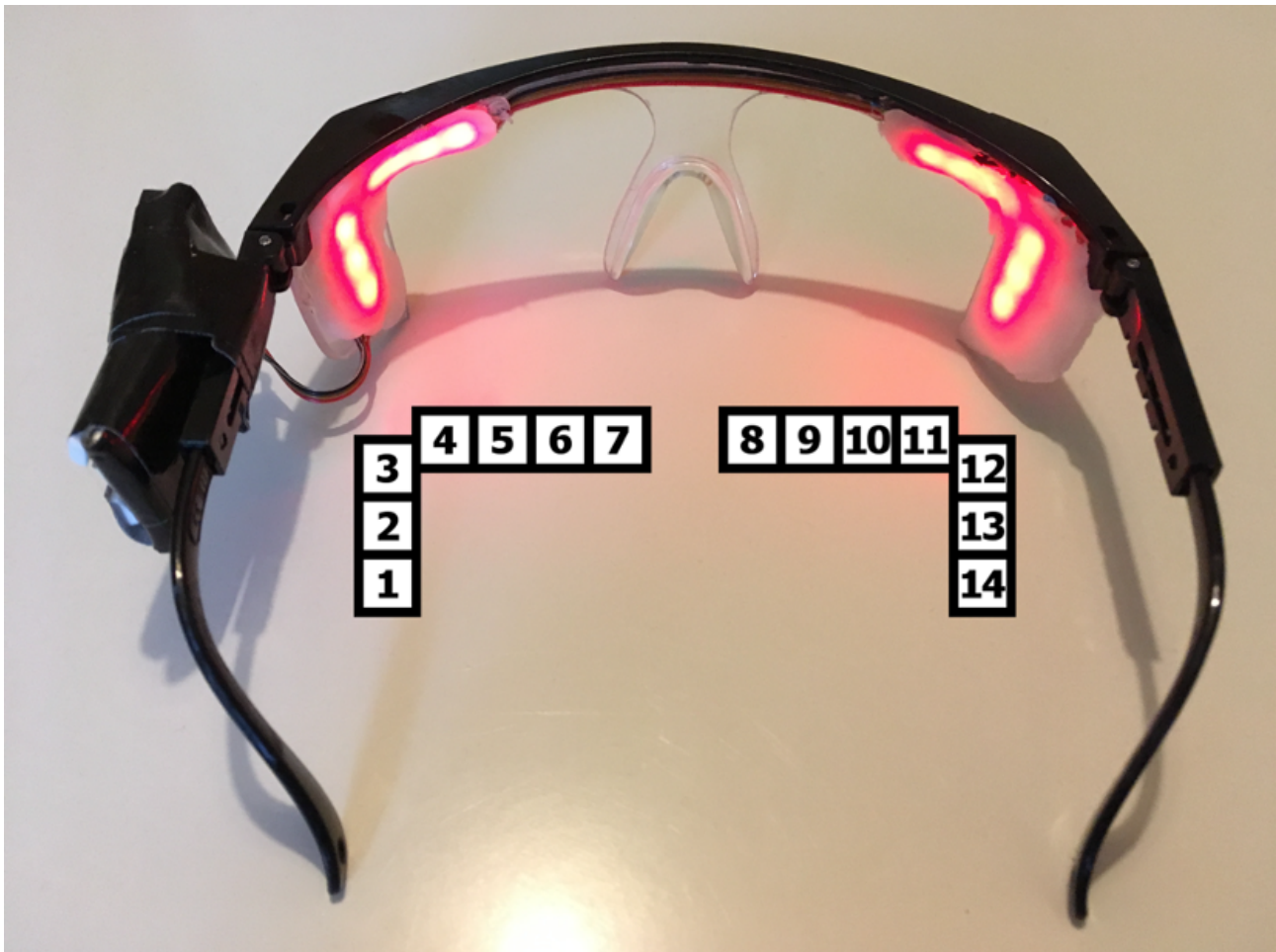
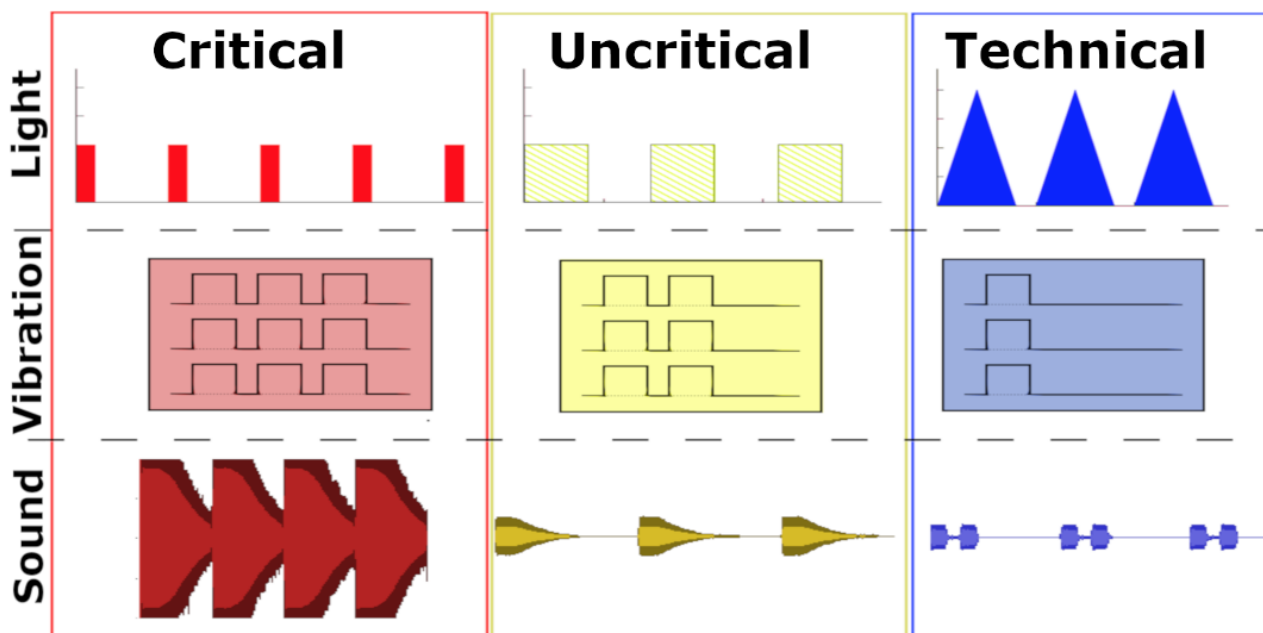


Figure 21. Lights, vibration, and sound patterns generated by the “peripheral light, tactile, and auditory” displays, respectively by Cobus and Heuten [26].



The research team asked 12 ICU nurses to identify several alarms using the *peripheral light*, *audible*, and *tactile* displays

individually versus the PM audible alarm. It was found that participants made significantly more errors with wearable

audible alarms and PM audible alarms. However, participants reported that they were used to, when hearing the PM alarm sound, to look at the PM display to identify the alarm’s cause. This indicates that as the purpose of the wearable’s display is to augment the PM, it would have been desirable to have the PM as part of the test scenario. In terms of IS identification time, although participants were faster when using the peripheral lights display in comparison with all others, participants raised concerns regarding the brightness of the lights of the peripheral light display, indicating that it was exhausting for the eyes and prone to triggering headaches.

Clueber et al [34] evaluated 2 displays designed for multiple patient monitoring: an HMD and an *auditory* display. The Vuzix M100 (Vuzix Corporation), which is an opaque monocular HMD that includes an earpiece for audio, was used for both displays. The design of the HMD interface can be seen in Figure 22. Using the Vuzix M100 earpiece, the auditory display presented time-compressed recordings of 500 milliseconds duration, verbalizing the variable name and variable level. For example, to convey that the values for SpO₂ and HR were normal, the auditory display verbalized *sat normal pulse normal*. The pitch and tone of the verbal cues were different depending on the severity of the patient’s state. A total of 57 undergraduate

students were randomly assigned to test 1 of the 3 groups: visual HMD, auditory HMD, or combined HMD. In terms of IS identification, participants using combined HMD or visual HMD alone performed significantly better than participants using auditory HMD. When asked to do a parallel activity (a precision computer task), which required constant visual attention, participants using the combined HMD performed better than participants using the visual HMD. Nonetheless, further studies involving clinicians are necessary to assess the *suitability* of these displays in critical care settings.

Pascale et al [35] also evaluated the use of HMD for continuous monitoring of multiple patients augmenting PM alarm sounds (Figure 23). In the first experiment with 76 undergraduate participants, it was verified that the PM alarms+HMD group responded to the alarms statistically significantly faster than participants in the PM alarm-only group. In the second experiment, the focus was to investigate if HMDs would improve SA. The authors developed an advanced auditory display (referred to as *notifications*) as a replacement for the PM alarms and tested it in conjunction with an improved version of the HMD. The notification display sounded in the earpiece of the HMD (Vuzix M100) when a variable value threshold was crossed, including when a variable value moved from abnormal to normal.

Figure 22. Information on the head-mounted displays by Klueber et al [34]. In this scenario, patients P-1, P-2, P-3, and P-4 have abnormal variables. Patient P-1 has exceeded the first high threshold for saturation of peripheral oxygen (SPO₂: 95%), and patient P-2 dropped below the second low threshold for SPO₂. Patient P-3 has exceeded the first high threshold for heart rate (a model of the concept presented in the paper). HR: heart rate; P: patient; SpO₂: oxygen saturation.

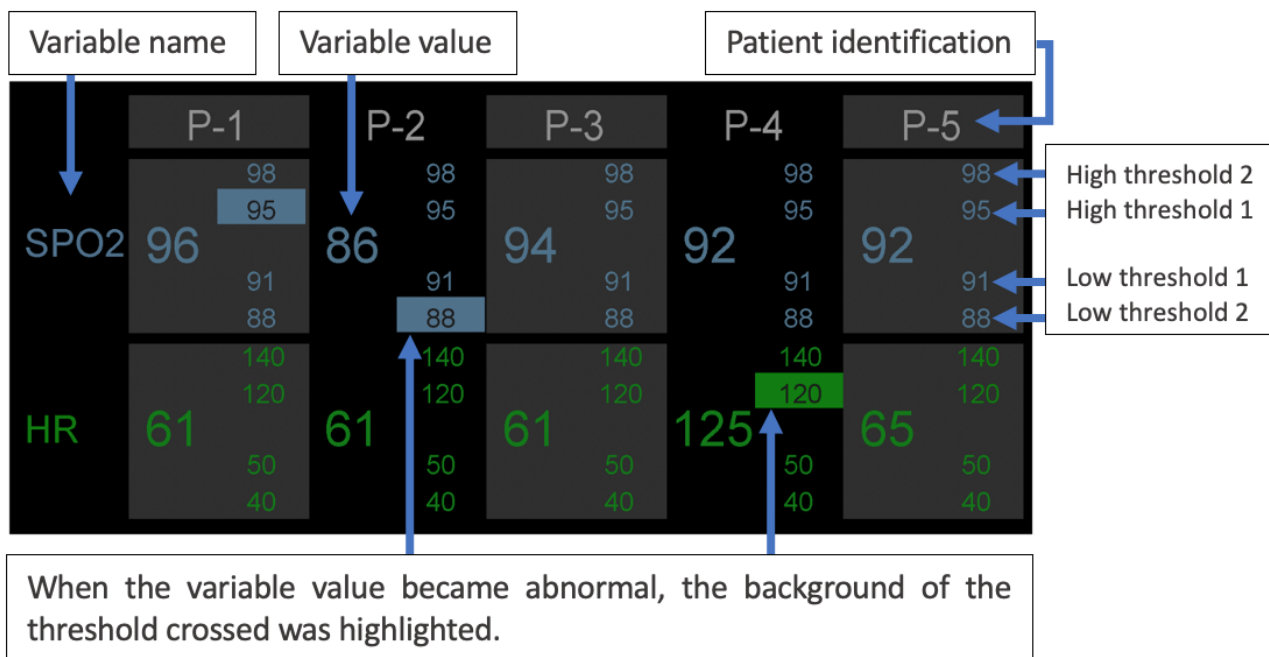
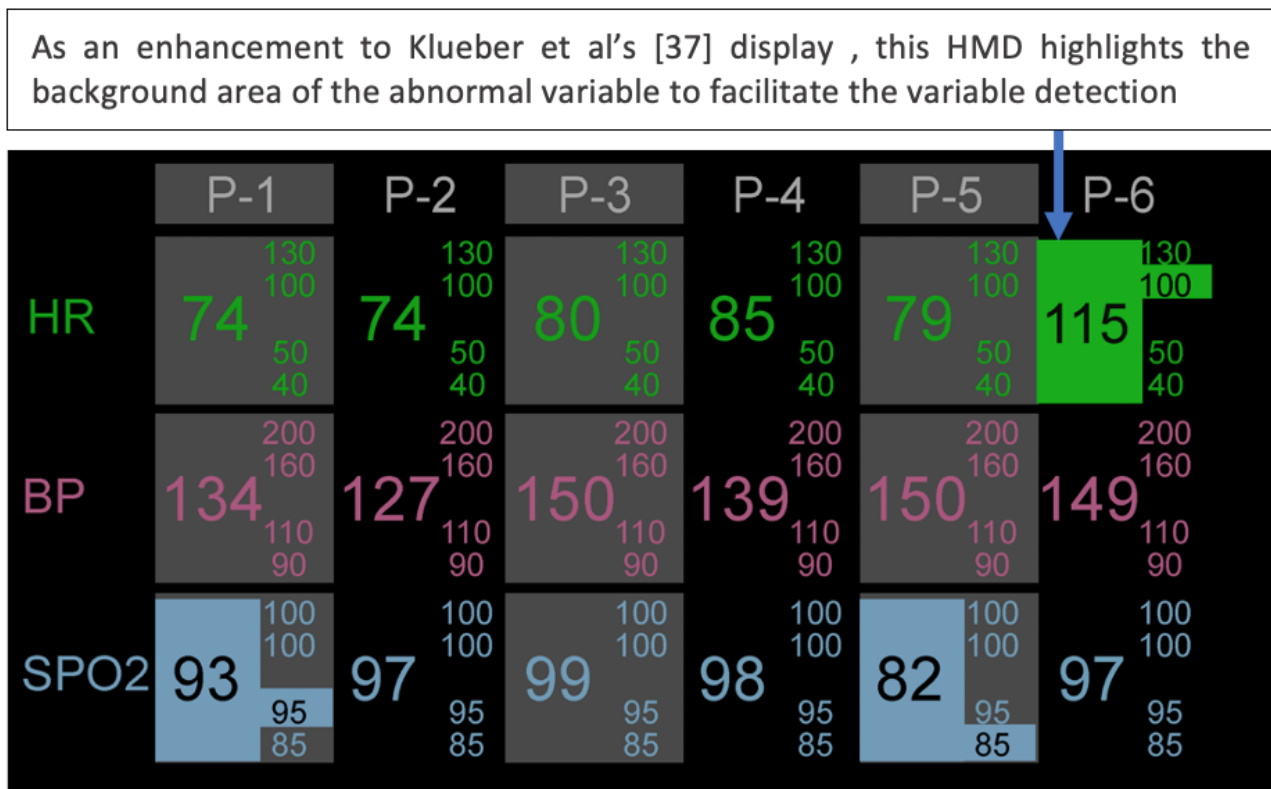


Figure 23. Continuous streams of patient data were presented on the head-mounted displays for up to 6 patients by Pascale et al [35]. The display was similar to the one from the study by Klueber et al [34], with the difference that this display also monitored blood pressure and abnormal values had their background highlighted. In this example, we can see that patients P-1, P-3, P-5, and P-6 have abnormal variables (a model of the concept presented in the paper). BP: blood pressure; P: patient; SpO₂: oxygen saturation.



A sound was played for each patient, based on their status, in the same order as the visual display. Therefore, notifications consisted of 6 consecutive sounds. The notification could be one of three 500 milliseconds tones: (1) a low-pitched beep with no tremolo indicating normal, (2) a medium-pitched beep with slow tremolo indicating that the first threshold was crossed for at least one vital sign for that patient, and (3) a high-pitched beep with faster tremolo indicating that the second threshold was crossed for at least one vital sign. In total, 13 second- and third-year nursing students participated in the experiment and tested the 3 display modalities: (1) PM alarm, (2) PM alarm+visual HMD, and (3) PM alarm+visual and auditory HMD. It was verified that participants answered the SA questions significantly more accurately, obtained higher scores on the ongoing patient assessment, and reported lower workload when they used the display modalities (2) and (3) in comparison to modality (1). Additionally, when using display modality (3), participants answered the SA questions significantly more accurately than when using modality (2).

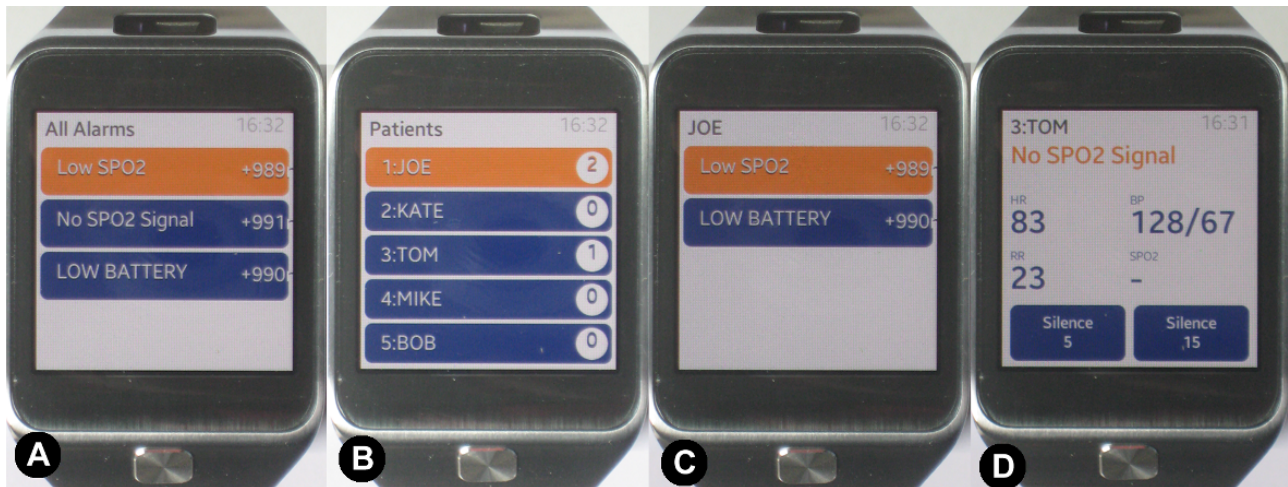
A summary of the results of HMD studies is presented in [Multimedia Appendix 2](#). Most studies were performed with

experienced clinicians as test subjects, which allowed researchers to test if these devices could improve clinicians' detection of clinical events during simulations. For this reason, *event detection*, *event detection time*, and *response time* were the main performance metrics used in these studies. As each study used different test events during the experiments and had different study designs, it is difficult to compare results across studies. However, most studies included the PM (screen or auditory alarm system) as a control display, which provides us with an opportunity to evaluate how the HMDs compared with the PM under the same test conditions.

Smartwatches

Another wearable that is starting to be explored for use in critical care patient monitoring is the smartwatch. McFarlan et al [38] tested the applicability of nurses using smartwatches when monitoring multiple patients simultaneously. A smartwatch app was developed to support ICU nurses to respond to alarms quickly. The smartwatch displayed alarms and patient vital signs and interacted with the actual PM, silencing it when an app button was pressed. The screens from the smartwatch app and explanation of the interface can be seen in [Figure 24](#).

Figure 24. Alarm system app running in a smartwatch with 4 screens by McFarlan et al [38]: (A) list of all alarms related to any patient monitored by the nurse, (B) list of the 5 patients monitored by the nurse, (C) list of all alarms for a selected patient, and (D) patient view with the alarm message on the top and the values for the patient's vital signs. The blue background indicates silenced alarms, and the orange background indicates alarms that are not silenced.



In total, 16 nurses undertook highly realistic multitasking within a simulated clinical unit using patient mannequins. The outcome measure used in this study was response time. The nurses received information and instructions about the patients and were asked to use their clinical judgment in deciding how and when to respond to alarms and call button events. Testing involved 20 simulated patients and 4 nurses; each nurse was assigned randomly to 5 patients. The experiment was divided into 2 parts (randomized across nurses): 90 minutes in the control conditions (using the PM only) and experimental conditions (with the smartwatch and PM).

It was observed that nurses responded to the alarms significantly faster with the PM+smartwatch display, with a median difference of -6.14 minutes (cumulative response time for all alarms in the experiment for each nurse) in the response time to important alarms or alerts. It was reported that the smartwatch display did not interfere with nurses' workflow. The smartwatch display gave the nurses the possibility of silencing the alarm without being near the PM and was rated positively in terms of usability; all nurses said they would use the system in real conditions.

Discussion

Tactile Displays

Overview of the Studies

Tactile displays were one of the first wearable devices investigated as a means to augment PMs in critical care medicine. This review found that tactile displays can potentially diminish the noise generated by PM alarms and enable the clinician to be alerted when the patient's vital signs cross alarm thresholds, without having to avert their gaze from the patient toward the PM.

Tactile Device Location and Number of Monitored Variables

Regarding the ideal location of a tactile device on the clinician's body, different authors had different design approaches. For

example, for a small number of monitored vital signs, the forearm and wrist were initially found to be suitable locations [18], with more recent studies proposing the upper arm as a better location for hygienic purposes [25,26]. In the case of a higher number of monitored vital signs, the waist was identified as a suitable location because of the greater number of factors, which must be accommodated [19-21]. Only 2 studies have tried *mapping* as a strategy to provide clinical information in a more user-friendly manner, reflecting best practices in usability engineering [39]. Ferris and Sarter [22] mapped the factors' location to the physical location of the corresponding variable, and Gomes et al [14] mapped the location of the factors according to the position of the respective variables on the PM display.

Subjects wearing tactile displays with a higher number of monitored variables (consequently, a higher number of different IS) are likely to achieve lower IS detection and identification compared with subjects wearing tactile displays to monitor fewer variables. *Response time* also seems to be profoundly affected by the number of variables monitored, with participants monitoring more than 3 variables taking generally longer to respond to the IS than participants monitoring a maximum of 2 variables. Therefore, using tactile displays to monitor a large number of variables might not be desirable.

Usability and Ergonomics Aspects

Regardless of the tactile device's positioning on the clinician's body or the number of monitored variables, *comfort* was a recurring theme, with several participants reporting discomfort or lack of mobility when wearing the displays [17,22,26]. It should be noted that the evaluated devices were prototypes fabricated in a research setting, and thus, the devices may not have been optimized from a design or fabrication perspective. A commercial product that incorporated these concepts would benefit from miniaturization using state-of-the-art manufacturing techniques and a full industrial design intervention and would thus be expected to overcome some of these usability issues. For instance, by using new technological components (wireless factors), McLanders et al [25] reported fewer discomfort issues

than previous studies. In conclusion, researchers must keep in mind that comfort has a significant impact on the perception of end users of a wearable device. The user may be reluctant to adopt a novel wearable technology that would enhance their performance if they do not feel comfortable wearing it.

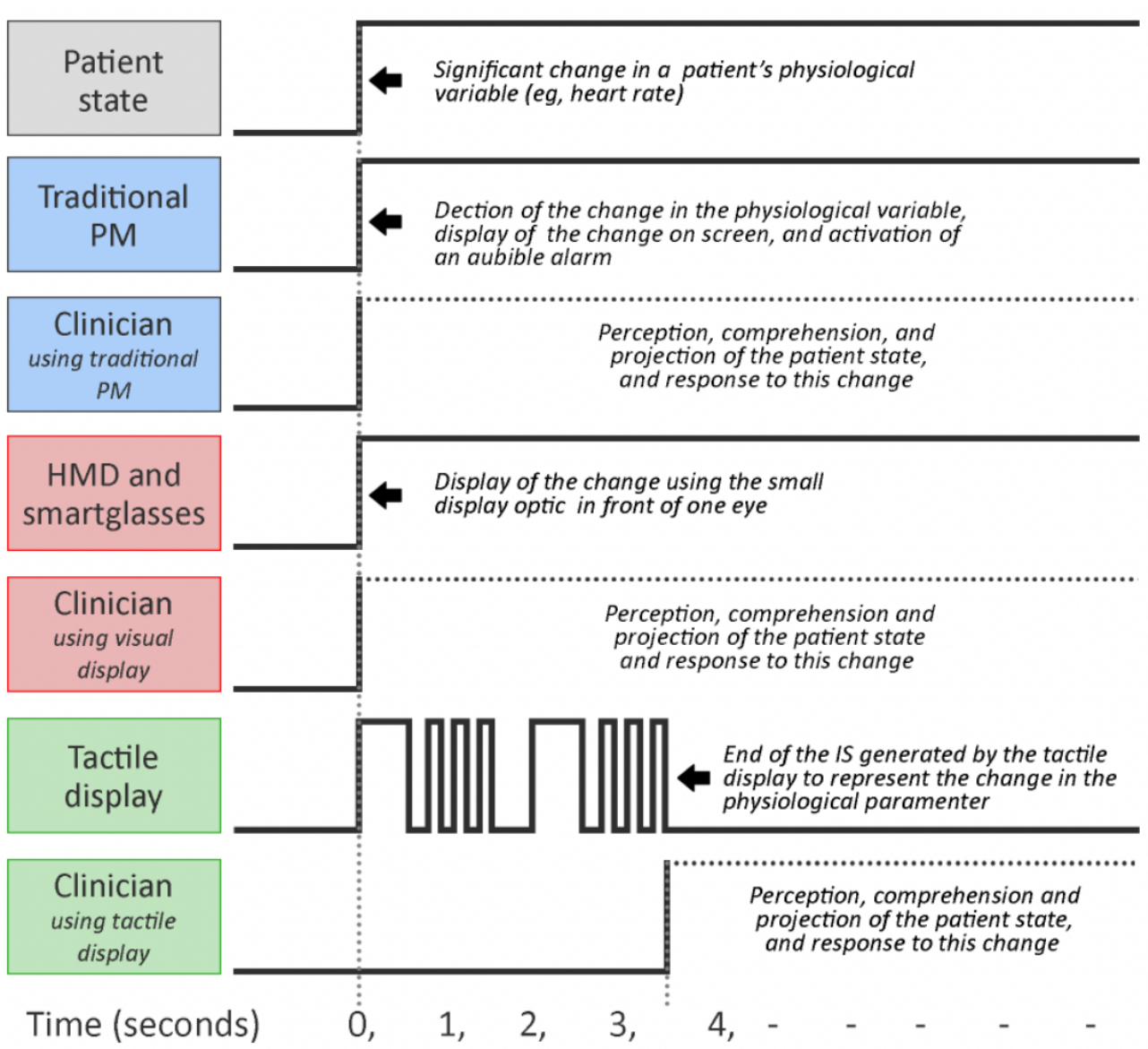
Performance Metrics

As the purpose of these devices is to augment critical care patient monitoring by increasing a clinician's ability to perceive a change in a variable, it is expected that IS *detection* will be higher when using the tactile display (to augment the PM). However, the number of IS detections does not necessarily correspond to the number of IS identifications, as it is possible to detect an IS but to then identify it incorrectly. Consequently, it is equally important or potentially even more critical to measure IS identification, which corresponds to the percentage of IS detected and correctly identified. Most studies have achieved more than 90% accuracy for both metrics (see [Multimedia Appendix 2](#) for more details). Therefore, the studies reviewed successfully demonstrated that conveying clinical information through tactile displays is possible. Nonetheless, the real significance of tactile displays for critical care can only be verified by conducting user testing with clinicians in real (or

close to real) contexts of use. For example, the IS detection and IS identification of their tactile display were considerably lower in the study by Dosani et al [20] than in the study by Ng et al [19], although the same tactile display was used in both studies. The context of use in the study by Dosani et al [20] was in a pediatric unit with patients, whereas in the study by Ng et al [19], the testing was conducted in a laboratory setting without patients.

Response time to a change in the patient state is one of the most common metrics used to assess clinicians' performance with a new display, and this metric can be affected by several factors (eg, clinician's experience, the tasks being performed in parallel with patient monitoring, and the monitoring device's physical location in the room). Regarding response time, tactile displays alone have a clear disadvantage compared with visual displays, as the IS from a tactile display requires more time to be conveyed in its entirety to the clinician. For example, the duration of a tactile display IS can range from 0.5 seconds [22] to 3.5 seconds [17] ([Figure 25](#)). It is important to note, however, that tactile displays are intended to augment PMs in a critical care setting. Therefore, response time can be reduced by looking at the PM as soon as they feel the initial stimuli on their skin without waiting for the full IS to be conveyed.

Figure 25. Timing diagram of patient state changes and clinician's response. With visual displays, the message is conveyed almost instantaneously. In contrast, in auditory and tactile displays, the message is conveyed through audio or vibration patterns, requiring more time to convey. HMD: head-mounted display; IS: interaction signal; PM: patient monitor.



HMDs and Smart Glasses

Overview of the Studies

HMDs have also been considered for augmenting PMs in critical care. Our review identified 10 studies in which potential end users were asked to wear HMDs in simulated conditions or real practice. Most experiments were not able to provide robust evidence that HMDs or smart glasses led to an improvement in the user's performance (eg, event detection, response time, and treatment efficiency) when used to monitor single patients during anesthesia or surgical settings [28,29,31]. However, promising results were achieved when HMDs were used to monitor multiple patients simultaneously [33,35].

Time Looking Toward the Patient

In all cases where the user's gaze was monitored, it was verified that clinicians spent significantly less time looking toward the PM and more time looking toward the patient, while maintaining the same level of SA [29-31]. These findings indicate that HMDs

can be useful from an ergonomics point of view in reducing the amount of clinician trunk and neck rotations associated with changing gaze, especially in environments where clinicians are physically constrained [29]. Beyond the possible comfort benefits of not averting their gaze from the patient, anesthesiologists could monitor changes in the patient's skin pallor, chest movement, and other signs more quickly under these conditions. Therefore, HMDs may also enhance patient safety.

Usability and Ergonomics

Only Sanderson et al [28] and Liu et al [29] (experiment 1) asked participants about their preference in terms of PM used. These two studies presented conflicting results, with most participants in the study by Sanderson et al [28] preferring to use the HMD and most participants in the study by Liu et al [29] preferring not to use the HMD. However, it is important to note that participants in the study of Sanderson et al [28] were not monitoring a simulated patient but were supervising

an actor who was monitoring a simulated patient, whereas in the study by Liu et al [29], participants were monitoring a simulated patient.

Regarding comfort and satisfaction, initial experiments with HMDs revealed a concern about the devices' weight and wired nature, which affected the user experience negatively [28-30]. In general, this problem was not reported in studies involving smart glasses because of their lightweight form and their incorporation of wireless technology, except for 1 study [33]. Most participants in the experiments with smart glasses stated that they would like to use them in their work, and they would recommend their use to colleagues. This level of acceptance was mainly observed among younger participants [31,32,37]. However, some participants commented that wearing the HMD could distract them when they were doing tasks that required focus [33]. Others reported that they had to mentally focus on the data displayed by HMDs to observe and interpret it [29], which could generate eye fatigue. More research investigating the correlation between the use of these systems and eye strain or fatigue needs to be conducted to verify this finding.

Smartwatches

Regarding the use of smartwatches for patient monitoring, McFarlan et al [38] have demonstrated promising results, which hopefully will lead to further studies investigating the feasibility and acceptance of these devices in the ICU. However, it is vital to keep in mind that the *bare below the elbows* policy, adopted in several hospitals in some jurisdictions, might impose an impediment in adopting these devices as they are currently designed. Researchers might have to identify ways of adjusting the design of these devices to be compliant with regulatory trends.

General Comments on Wearable Devices for Critical Care

Most wearable devices (tactile displays, HMDs, or smartwatches) for critical care medicine (anesthesia, surgery, or the ICU) are intended to be used to augment current monitoring practices and not as a replacement. It is expected that, by adding another source of information, the likelihood of nurses and doctors missing a clinical event will be reduced, and they will be able to detect abnormalities faster. Researchers reported significant improvements in various metrics when participants used the PM plus a wearable display in comparison with participants using a PM only [17,28-33,35,38]. Some researchers explored the benefits of conveying information through multiple channels by developing multisensorial displays. These prototypes integrate, for example, auditory and tactile stimuli [27] or auditory, tactile, and visual stimuli [30] to inform the ICU nurse about patient alarms, thus increasing their SA and reducing alarm fatigue. Figures 3 and 4 illustrate how wearables can use different senses as communication channels. Beyond performance, conveying information through multiple channels might also be important for safety reasons if one of the wearable communication channels fails. Nonetheless, given their potential to overwhelming the users, the *suitability* of multisensorial wearable devices for critical care monitoring needs to be further investigated under conditions that reflect the proposed context of use.

It is important to note that enhancing the detection and identification of variable changes using wearable displays does not necessarily automatically translate into enhanced patient outcomes. Ultimately, clinical trials would be required to effectively demonstrate improved outcomes for patients.

Limitations

Although all the studies reviewed presented wearable devices to augment patient monitoring in critical care, the studies diverged significantly in terms of the intended uses of the devices and the study designs adopted to evaluate them. Therefore, we acknowledge that, because of this heterogeneity in the literature, the ability to synthesize findings was reduced.

Conclusions and Recommendations

This study aimed to review the literature on state-of-the-art wearable devices for critical care vital sign monitoring and to present the findings with a critical analysis of the usability and human factors performance of these devices. A total of 20 studies were identified: 9 on tactile displays, 9 on HMDs, 1 on a hybrid tactile and HMD display, and 1 on smartwatch displays. The studies on tactile displays have successfully demonstrated that these devices can be used to convey information on patient vital signs to critical care nurses and doctors. However, at this point, there is not enough evidence to indicate that tactile displays can positively impact the user's performance compared with the PM only, and thus, more testing with critical care nurses and doctors is necessary. The issue of discomfort has been a significant challenge to be overcome in the design of these devices, with many participants reporting some level of discomfort when wearing tactile displays. Researchers should attempt to create more *finished* prototypes, ideally developed following an industrial design exercise, although this process can add significantly to the research cost.

The studies involving smart glasses for critical care patient monitoring have successfully demonstrated that these devices overcame the discomfort-related issues associated with their predecessor's HMDs. When monitoring patients wearing HMDs or smart glasses, it was found that doctors spent more time looking at the patient and the surgical field than at the PM, compared with the case when they are using a PM only. This outcome can be potentially useful from an ergonomics point of view, in reducing the amount of trunk and neck rotations associated with changing gaze, especially in environments where clinicians are physically constrained. Additionally, this outcome can be useful from a patient safety point of view, in reducing the amount of time when the clinician is not directly observing the patient.

On the basis of our experience of reviewing these studies, we believe that future researchers can improve their investigations of novel wearable devices for critical care vital sign monitoring by (1) conducting experiments involving control (PM) and experimental displays, tested using the intended end users; (2) paying particular attention to comfort and technical performance aspects of their devices; and (3) using postexperiment interviews to enable the study to benefit from a qualitative analysis of issues such as comfort, user experience, and the likelihood of adopting the technology.

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Authors' Contributions

This review was conducted by a multidisciplinary team of engineers, health scientists, nurses, anesthesiologists, human factors specialists, and medical consultants. EA, LQ, RH, and GOL were responsible for defining the methodology, extracting the data, and writing the manuscript. DB, SC, FK, MS, JL, PP, and AB reviewed the manuscript and provided feedback related to the medical aspects. EF, MK, POC, and DOH reviewed the manuscript to provide support with human factors expertise.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Terminology used in the review.

[DOCX File , 16 KB - [humanfactors_v8i2e16491_app1.docx](#)]

Multimedia Appendix 2

Summary of the experiments reviewed.

[DOCX File , 35 KB - [humanfactors_v8i2e16491_app2.docx](#)]

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Abbreviations

BP: blood pressure

CRS: comfort rating scale

HMD: head-mounted display

HR: heart rate

ICU: intensive care unit

IS: interaction signal

PM: patient monitor

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-analyses

SA: situation awareness

SUS: system usability scale

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Review

Research Trends in Artificial Intelligence Applications in Human Factors Health Care: Mapping Review

Onur Asan¹, PhD; Avishek Choudhury¹, MSc

School of Systems and Enterprises, Stevens Institute of Technology, Hoboken, NJ, United States

Corresponding Author:

Onur Asan, PhD

School of Systems and Enterprises

Stevens Institute of Technology

1 Castle Point Terrace

Hoboken, NJ, 07030

United States

Phone: 1 4145264330

Email: oasan@stevens.edu

Abstract

Background: Despite advancements in artificial intelligence (AI) to develop prediction and classification models, little research has been devoted to real-world translations with a user-centered design approach. AI development studies in the health care context have often ignored two critical factors of ecological validity and human cognition, creating challenges at the interface with clinicians and the clinical environment.

Objective: The aim of this literature review was to investigate the contributions made by major human factors communities in health care AI applications. This review also discusses emerging research gaps, and provides future research directions to facilitate a safer and user-centered integration of AI into the clinical workflow.

Methods: We performed an extensive mapping review to capture all relevant articles published within the last 10 years in the major human factors journals and conference proceedings listed in the “Human Factors and Ergonomics” category of the Scopus Master List. In each published volume, we searched for studies reporting qualitative or quantitative findings in the context of AI in health care. Studies are discussed based on the key principles such as evaluating workload, usability, trust in technology, perception, and user-centered design.

Results: Forty-eight articles were included in the final review. Most of the studies emphasized user perception, the usability of AI-based devices or technologies, cognitive workload, and user’s trust in AI. The review revealed a nascent but growing body of literature focusing on augmenting health care AI; however, little effort has been made to ensure ecological validity with user-centered design approaches. Moreover, few studies (n=5 against clinical/baseline standards, n=5 against clinicians) compared their AI models against a standard measure.

Conclusions: Human factors researchers should actively be part of efforts in AI design and implementation, as well as dynamic assessments of AI systems’ effects on interaction, workflow, and patient outcomes. An AI system is part of a greater sociotechnical system. Investigators with human factors and ergonomics expertise are essential when defining the dynamic interaction of AI within each element, process, and result of the work system.

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KEYWORDS

artificial intelligence; human factors; health care systems; ecological validity; usability; trust; perception; workload

Introduction

Influx of Artificial Intelligence in Health Care

The influx of artificial intelligence (AI) has been shifting paradigms for the last decade. The term “AI” has been often used and interpreted with different meanings [1], and there is a

lack of consensus regarding AI’s definition [2]. In general, AI can be defined as a computer program or intelligent system capable of mimicking human cognitive function [3]. Over the years, the capabilities and scope of AI have substantially increased. AI now ranges from algorithms that operate with predefined rules and those that rely on if-then statements (decision tree classifiers) [4] to more sophisticated deep-learning

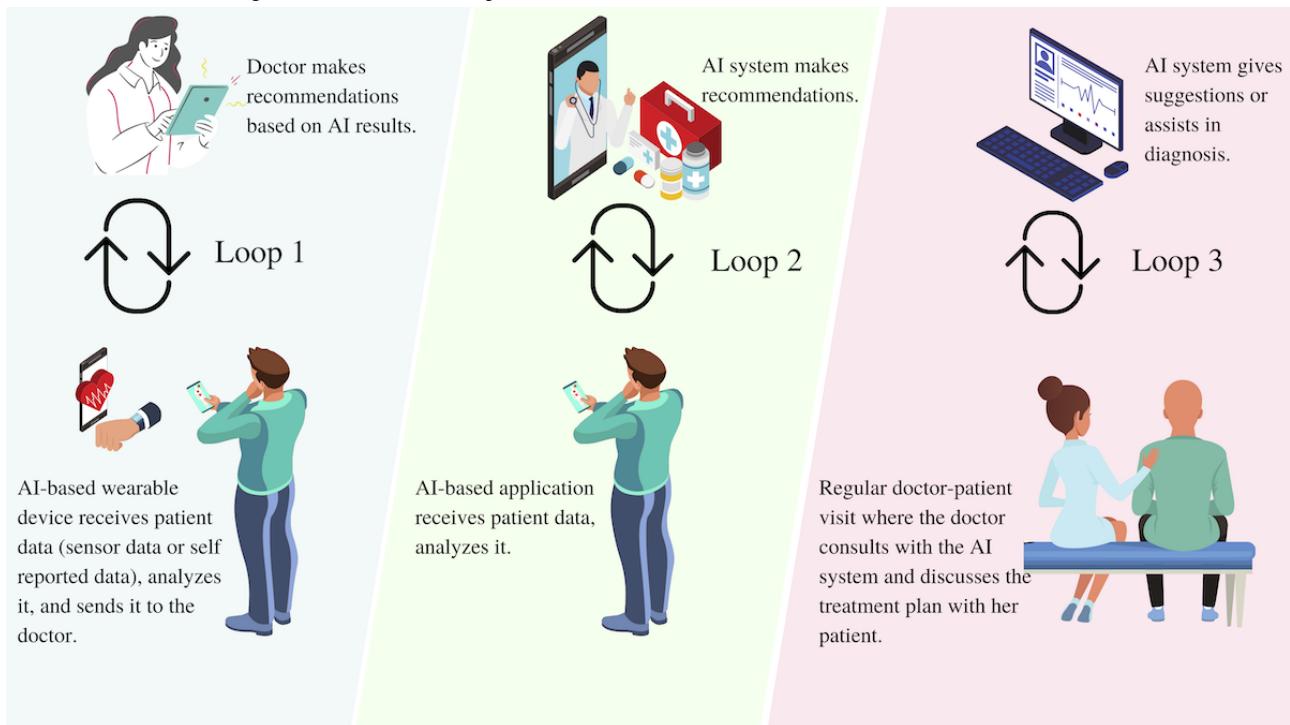
algorithms that have the capabilities to automatically learn and improve through statistical analyses of large datasets [5,6]. There have been many studies and advancements with AI as it continues to evolve in numerous domains, including health care. AI applications such as MelaFind, a virtual assistant software, and IBM Watson have been introduced to improve health care systems, foster patient care, and augment patient safety [7]. AI applications have been developed and studied for every stakeholder in health care, including providers, administrators, patients, families, and insurers. In some specific areas such as radiology and pathology, there are strong arguments that AI systems may supersede doctors as a result of studies showing that AI algorithms outperformed doctors in accurately detecting cancer cells [8-10].

Further, developments in AI-enabled health information technologies (eg, AI-enabled electronic health records [EHRs] or clinical decision support systems) have benefitted from the availability of big data to predict clinical outcomes and assist providers in parsing through their EHRs to find individual pieces of medical information [11]. Despite AI having great potential, it is still in its infancy. The existing clinical AI systems are far from perfect for several well-known reasons, including (a) discriminatory biases coming from the input data; (b) lack of transparency in AI decisions, particularly neural networks, due to the black-box nature; and (c) sensitivity of the resulting decisions to the input data [6,12].

Typical AI-User Interactions

AI systems are complex in the sense of being a black box for the users who might not have adequate expertise in statistics or computer science to be able to comprehend the functioning of AI. Thus, AI can undesirably complicate the relationships between users and computer systems if not well designed. Unlike other health care technologies, AI can interact (eg, through chatbots, automated recommender systems, health apps) with clinicians and patients based on the inputs (feedback) that

it receives from the user, thus creating what we refer to as “the interaction loop.” Unlike non-AI technologies, AI’s output (result generated by the AI) largely depends on the information fed into it; for instance, in AI-based reinforcement learning [13], the system may learn and adapt itself based on user input. Therefore, the human-AI interaction may influence the human as well as the AI system: the user feeds AI with some information; the AI learns from this information, performs analyses, and sends an output to the user; the user receives the output, comprehends it, and acts accordingly; and the new data generated by the user’s action goes back to the AI. [Figure 1](#) illustrates three fundamental and typical interaction loops highlighting fundamental plausible transactions among clinicians, patients, and the AI system, in which the AI technology (such as Apple Watch) continuously measures the user’s health information (heart rate, oxygen level) and sends the data to the user’s health care provider. The care provider can then make treatment plans or clinical recommendations based on the AI results, which will then influence user health or health-related behavior (Loop 1). Other common user-AI interactions can be observed in online health services in which the user interacts with an AI-enabled chatbot for preliminary diagnoses (Loop 2). The third, but less common, user-AI interaction is when a doctor and patient together leverage an AI system for obtaining a better diagnosis in a clinical environment (Loop 3). For all of these applications, it is essential for the users to make a correct interpretation of AI outcomes, and to have a basic understanding of AI requirements and limitations. The optimum and successful user-AI interaction depends on several factors, including the physical (eg, timely access to technology, and visual and hearing ability, particularly of patients), cognitive (eg, ability to comprehend AI functioning, ability to reason and use AI-enabled devices), and emotional (eg, current state of mind, willingness to use AI, prior experience with AI technology) resources of people (eg, health professionals and caregivers).

Figure 1. User-artificial intelligence (AI) interaction loops.

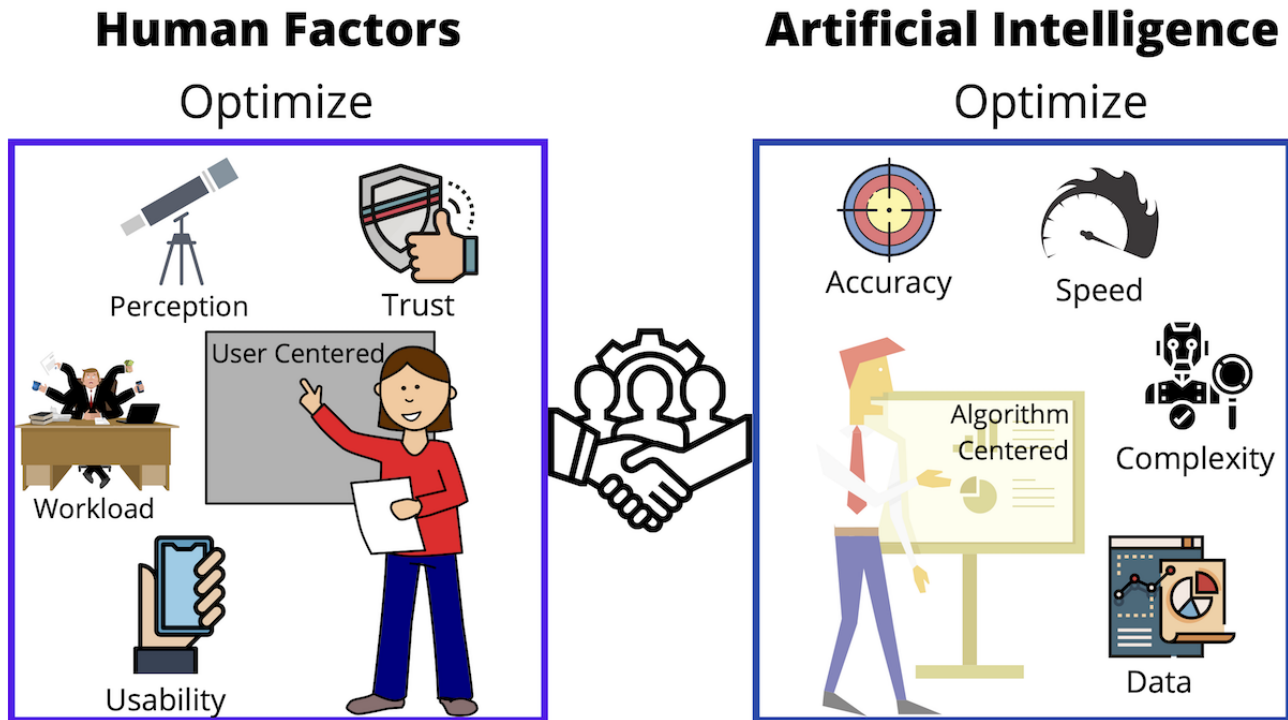
Efforts to Improve AI and the Essential Role of Human Factors

The developers of health care AI apps have primarily focused on AI's analytical capabilities, accuracy, speed, and data handling (see Figure 2) and have neglected human factors perspectives, which lead to poorly designed apps [14]. Although recent studies have reported the impact of biased data [15], as well as interpretability, interoperability, and lack of standardization [7,16] on AI outcomes, very few have acknowledged the need to assess the interactions among AI, clinicians, and care recipients.

Recently, as acknowledged in the Annual Meetings of the Human Factors Ergonomics Society [17,18], increasing autonomous activities in health care can pose risks and concerns regarding AI. Therefore, there is a need to integrate human factors and ergonomics (HFE) principles and methods into developing AI-enabled technologies for better use, workflow integration, and interaction. In health care AI research, two

factors have not been sufficiently addressed by researchers, namely ecological validity and human cognition, which may create challenges at the interface with clinicians as well as the clinical environment and lead to errors. Moreover, there is insufficient research focusing on improving the human factors, mainly (a) how to ensure whether clinicians are implementing the AI correctly, (b) the cognitive workload it imposes on clinicians working in stressful environments, and (c) its impact on clinical decision-making and patient outcome. The inconvenient truth is that most of the AI showing prominent ability in research and the literature is not currently executable in a clinical environment [19,20]. Therefore, to better identify the current state of HFE involvement in health care AI, we performed a mapping review of studies published in major human factors journals and proceedings related to AI systems in health care. The aim of the mapping review was to highlight what has been accomplished and reported in HFE journals and discuss the roles of HFE in health care AI research in the near future, which can facilitate smoother human-system interactions.

Figure 2. Illustrating some of the research objectives of experts in human factors and artificial intelligence.



Methods

Design and Data Source

We performed a mapping review to explore the trending and initial areas regarding health care AI research in HFE publications. Our protocol was registered with the Open Science Framework on October 2, 2020 [21]. Mapping reviews are well-developed approaches to cover the representative literature (not exhaustive) for exploring and demonstrating trends in a given topic and time duration [22]. In this study, we selected major human factors journals and conferences that potentially publish health care-related work as our data source. Our selection of journals and conferences was guided by the “Human Factors and Ergonomics” category of the Scopus Master List and Scimago Journal & Country Rank. We also added two journals that potentially publish patient safety-related human factors work: *Journal of Patient Safety* and *BMJ Quality and Safety*. In total, we explored 24 journals and 9 conference proceedings (see [Multimedia Appendix 1](#)). All the authors approved the final list of journals and conferences with consensus.

Inclusion and Exclusion Criteria

We performed an extensive manual search to capture all relevant articles published in English within the last 10 years (January 2010 to December 2020) in the journals and conference proceedings listed in [Multimedia Appendix 1](#). In each published volume, we searched for studies reporting qualitative or quantitative findings in the context of AI in health care. The selected studies needed to (1) be framed in the context of health care; (2) cover an AI algorithm or AI-enabled technology such as machine learning, natural language processing, or robotics; and (3) report either qualitative or quantitative findings/outcomes. We only included journal papers and full

conference proceeding papers. Other materials such as conference abstracts, editorials, book chapters, poster presentations, perspectives, study protocols, review papers, and gray literature (eg, government reports and policy statement papers) were excluded.

Paper Selection and Screening

Articles in the journal and conference list were manually screened by two reviewers (AC and a research assistant) based on titles and abstracts using one of the inclusion criteria (ie, to be framed in the context of health care). We exported all of the retrieved publications to Sysrev software. In the second step, we excluded all ineligible publications (eg, reviews, short abstracts, and posters), as explained in the preceding section. In the last step, two reviewers (AC and a research assistant) independently screened all of the selected full papers based on the remaining two inclusion criteria: (1) covering an AI algorithm or AI-enabled technology such as machine learning, natural language processing, or robotics; and (2) reporting either qualitative or quantitative findings/outcomes. The reviewers also confirmed that the studies were framed in a health care context. The reviewers achieved 82% agreement. The lead researcher (OA) then resolved all conflicts, screened all of the shortlisted full-text articles, and finalized the article selection.

Data Extraction and Analysis

We followed a similar data extraction approach and analysis as reported by Holden et al [23]. Metadata (author names, the title of the paper, abstract) for each of the included articles were recorded in a standard Excel sheet. In our analysis, both authors (AC and OA) coded each included paper on different dimensions such as (1) sample/participant type, (2) AI system used, (3) source of data collection, and (4) objective and outcomes. Studies were also discussed based on the HFE principles such as evaluating workload, usability, trust in technology,

perception, and user-centered design. These HFE principles and subcategories for the dimensions were derived from the final selected papers and were checked for face validity by the researchers. We iteratively worked on the data extraction process and revised the categories to achieve a final consensus.

Results

Summary of Included Studies

Figure 3 illustrates the screening and selection process. As a result of screening 24 selected journals and 9 conference proceedings (Multimedia Appendix 1), we finalized 48 articles matching our inclusion criteria, which were included in the scoping review with consensus from all reviewers. These 48 articles were published in 10 journals and 3 conference proceedings, as illustrated in Figure 4.

Figure 3. Selection and exclusion process. AI: artificial intelligence.

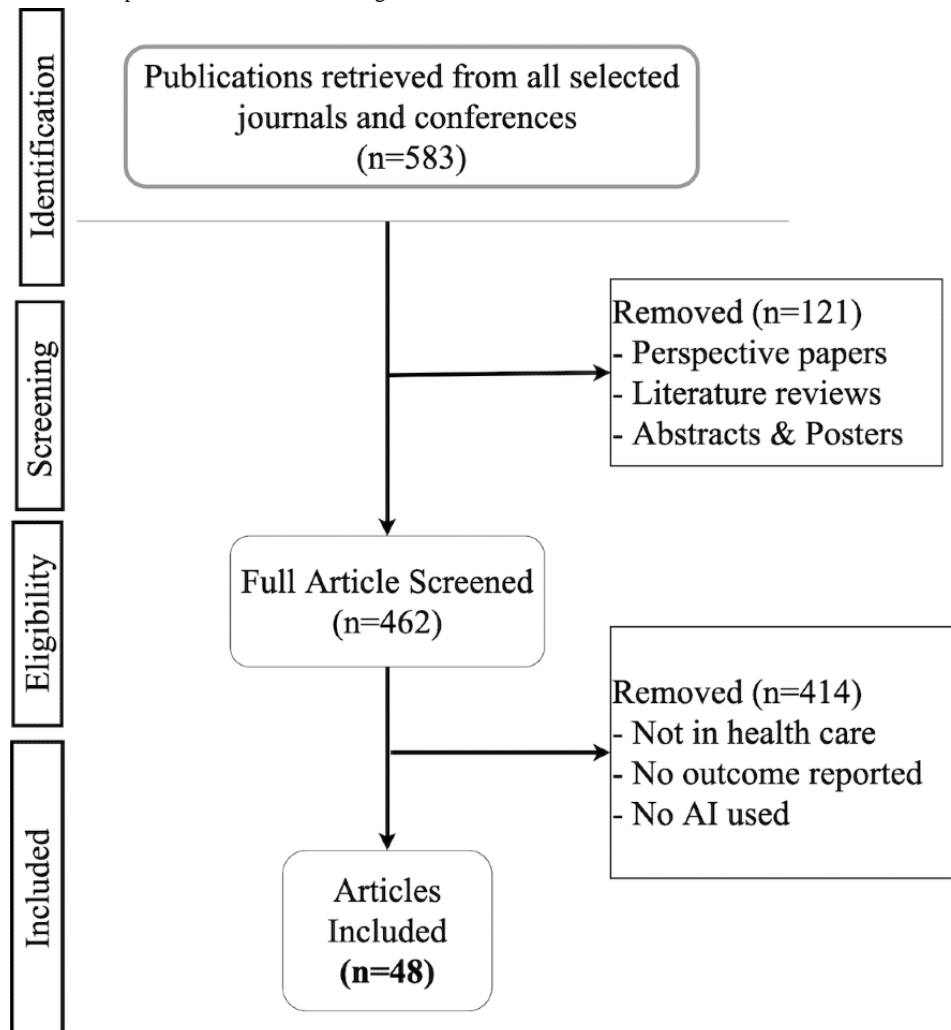


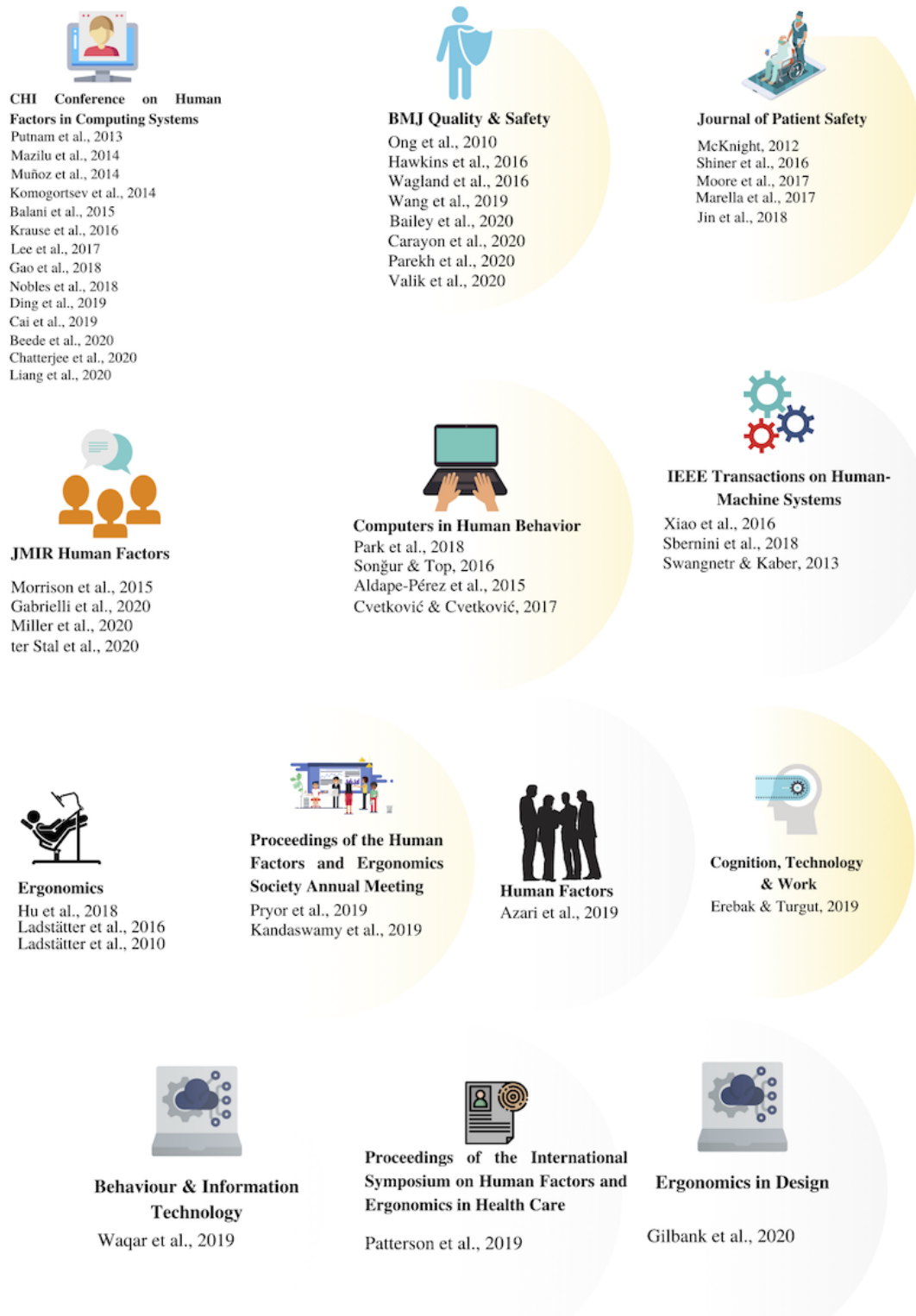
Figure 4. Overview of selected publications and their venues.

Table 1 shows the following dimensions: (1) objective of the study; (2) overall methods used, including the ethnographic/quantitative analysis methods adopted, and the type of data (“Methods and Data” column); (3) study participants (user of the AI system); and (4) primary outcome/findings of the study. Most studies involved human participants such as clinicians and patients (n=33) as shown in the “Study Participants” column in Table 1. However, some studies used

data from online sources such as Reddit, Twitter, and clinical databases. Approximately 26 studies conducted surveys and interviews to gain insight from study participants, as shown in the “Methods and Data” column. Some studies emphasized algorithms to analyze video, text, and sensor data. Overall, we observed that most studies evaluated AI from the user perspective and others leveraged AI to augment user performance.

Table 1. Evidentiary table of selected publications, summarizing their objectives, methods, participants, and outcomes (N=48).

| Study | Objective | Methods and Data | Study participants | Immediate outcome observed |
|------------------------------|--|---|--------------------------------------|---|
| Aldape-Pérez et al [24] | To promote collaborative learning among less experienced physicians | Mathematical/ numerical data | NA ^a (online database) | Delta Associative Memory was effective in pattern recognition in the medical field and helped physicians learn |
| Azari et al [25] | To predict surgical maneuvers from a continuous video record of surgical benchtop simulations | Mathematical/video data | 37 surgeons | Machine learning's prediction of surgical maneuvers was comparable to the prediction of robotic platforms |
| Balani and De Choudhury [26] | To detect levels of self-disclosure manifested in posts shared on different mental health forums on Reddit | Mathematical/text data | NA (Reddit posts from 7248 users) | Mental health subreddits can allow individuals to express or engage in greater self-disclosure |
| Cai et al [27] | To identify the needs of pathologists when searching for similar images, retrieved using a deep-learning algorithm | Survey study: Mayer's trust model, NASA-TLX, questions for mental support for decision-making, diagnostic utility, workload, future use, and preference | 12 pathologists | Users indicated having greater trust in SMILY; it offered better mental support, and providers were more likely to use it in clinical practice |
| Cvetković and Cvetković [28] | To analyze the influence of age, occupation, education, marital status, and economic condition on depression in breast cancer patients | Interview study using the Beck Depression Inventory guide | 84 patients | Patient age and occupation had the most substantial influence on depression in breast cancer patients |
| Ding et al [29] | To learn about one's health in everyday settings with the help of face-reading technology | Interview study: specific questions about time and location of usage, users' perceptions and interpretations of the results, and intentions to use it in the future | 10 users | Technology acceptance was hindered due to low technical literacy, low trust, lack of adaptability, infeasible advice, and usability issues |
| Ereback and Turgut [30] | To study human-robot interaction in elder care facilities | Survey study: Godspeed anthropomorphism scale, trust checklist [31], scales from [32], and automated functions of [33]. | 102 caregivers | No influence of anthropomorphism was detected on trust in robots; providers who trusted robots had more intention to work with them and preferred a higher automation level |
| Gao et al [34] | To detect motor impairment in Parkinson disease via implicitly sensing and analyzing users' everyday interactions with their smartphones | Mathematical; sensor data | 42 users | Parkinson disease was detected with significantly higher accuracy when compared to a clinical reference |
| Hawkins et al [35] | To measure the patient-perceived quality of care in US hospitals | Survey study; hospitals were asked to provide feedback regarding their use of Twitter for patient relations | NA (Tweets) | Patients use Twitter to provide input on the quality of hospital care they receive; almost half of the sentiment toward hospitals was, on average, favorable |
| Hu et al [36] | To detect lower back pain from body balance and sway performance | Mathematical; sensor data | 44 patients and healthy participants | The machine-learning model was successful in identifying patients with back pain and responsible factors |
| Jin et al [37] | To identify, extract, and minimize medical error factors in the medication administration process | Mathematical/text data | NA (data from 4 hospitals) | The proposed machine-learning model identified 12 potential error factors |
| Kandaswamy et al [38] | To predict the accuracy of an order placed in the EHR ^b by emergency medicine physicians | Mathematical/text and numerical data | 53 clinicians | Machine-learning algorithms identified error rates in imaging, lab, and medication orders |
| Komogortsev and Holland [39] | To detect mild traumatic brain injury (mTBI) via the application of eye movement biometrics | Mathematical/video data | 32 patients and healthy participants | Supervised and unsupervised machine learning classified participants with detection scores ≤ -0.870 and ≥ 0.79 as having mTBI, respectively |
| Krause et al [40] | To support the development of understandable predictive models | Mathematical/ numerical data | 5 data scientists | Interactive visual analytic systems helped data scientists to interpret predictive models clinically |

| Study | Objective | Methods and Data | Study participants | Immediate outcome observed |
|-----------------------|--|---|---|---|
| Ladstatter et al [41] | To measure the feasibility of artificial neural networks in analyzing nurses' burnout process | Survey study: Nursing Burnout Scale Short Form | 465 nurses | The artificial neural network identified personality factors as the reason for burnout in Chinese nurses |
| Ladstatter et al [42] | To assess whether artificial neural networks offer better predictive accuracy in identifying nursing burnouts than traditional statistical techniques | Survey study: Nursing Burnout Scale Short Form | 462 nurses | Artificial neural networks identified a strong personality as one of the leading causes of nursing burnout; it produced a 15% better result than traditional statistical instruments |
| Lee et al [43] | To determine how wearable devices can help people manage their itching conditions | Interview study: user experience and acceptance of the device | 40 patients and 2 dermatologists | Machine learning-based itchtector algorithm detected scratch movement more accurately when patients wore it for a longer duration |
| Marella et al [44] | To develop a semiautomated approach to screening cases that describe hazards associated with EHRs from a mandated, population-based reporting framework for patient safety | Mathematical/text and numerical data | NA | Naïve Bayes Kernel resulted in the highest classification accuracy; it identified a higher proportion of medication errors and a lower proportion of procedural error than manual screening |
| Mazilu et al [45] | To evaluate the impact of a wearable device on gait assist among patients with Parkinson disease | Interview study: asking about usability, feasibility, comfort, and willingness to use Gait Assist. | 18 patients and 5 healthy participants | AI ^c -based Gait Assist was perceived as useful by the patients. Patients reported a reduction in freezing of gait duration and increased confidence during walking |
| McKnight [46] | To analyze patient safety reports. | Mathematical/text data | NA | Natural language processing improved the classification of safety reports as Fall and Assault; it also identified unlabeled reports |
| Moore et al [47] | To evaluate natural language processing's performance for extracting abnormal results from free-text mammography and Pap smear reports. | Mathematical/text data | NA | The performance of natural language processing was comparable to a physician's manual screening |
| Morrison et al [48] | To evaluate the usability and acceptability of ASSESS MS. | Interview study: feedback questionnaires, usability scales | 51 patients, 6 neurologists, and 6 nurses | ASSESS MS was perceived as simple, understandable, effective, and efficient; both patients and doctors agreed to use it in the future |
| Muñoz et al [49] | To augment the relationship between physical therapists and their patients recovering from a knee injury, using a wearable sensing device | Interview study to understand how physical therapists work with their patients; user interface design considering usability and comfort | 2 physical therapists | Machine learning-based wearable device correctly identified exercises such as leg lifts (100% accuracy) but also incorrectly identified three nonleg lifts as successfully performed leg lifts (3/18 false positives) |
| Nobles et al [50] | To identify periods of suicidality | Survey study: evaluating psychology students' communication habits using electronic services | 26 patients | The machine-learning model accurately identified 70% of suicidality when compared to the default accuracy (56%) of a classifier that predicts the most prevalent class |
| Ong et al [51] | To automatically categorize clinical incident reports | Mathematical/text and numerical data | NA | Naïve Bayes and support vector machine correctly identified handover and patient identification incidents with an accuracy of 86.29%-91.53% and 97.98%, respectively |
| Park et al [52] | To compare discussion topics in publicly accessible online mental health communities for anxiety, depression, and posttraumatic stress disorder | Mathematical/text data | NA | Depression clusters focused on self-expressed contextual aspects of depression, whereas the anxiety disorders and posttraumatic stress disorder clusters addressed more treatment- and medication-related issues |
| Patterson et al [53] | To understand how transparent complex algorithms can be used for predictions, particularly concerning imminent mortality in a hospital environment | Interview study: group discussion | 3 researchers | All participants gave contradicting responses |

| Study | Objective | Methods and Data | Study participants | Immediate outcome observed |
|--------------------------|--|---|--|--|
| Pryor et al [54] | To analyze the use of a software medical decision aid by physicians and nonphysicians | Observation study; the study indirectly tested the usability and users' trust in the device | 34 clinicians and 32 nonclinical individuals | Physicians did not follow tool recommendations, whereas nonphysicians used diagnostic support to make medical decisions |
| Putnam et al [55] | To describe a work-in-progress that involves therapists who use motion-based video games for brain injury rehabilitation | Interview study to understand therapists' experiences, opinions, and expectations from motion-based gaming for brain injury rehabilitation | 11 therapists and 34 patients | Identifying games that were a good match for the patient's therapeutic objectives was important; traditional therapists' goals were concentration, sequencing, coordination, agility, partially paralyzed limb utilization, reaction time, verbal reasoning, and turn-taking |
| Sbernini et al [56] | To track surgeons' hand movements during simulated open surgery tasks and to evaluate their manual expertise | Mathematical/sensor data | 18 surgeons | Strategies to reduce sensory glove complexity and increase its comfort did not affect system performance substantially |
| Shiner et al [57] | To identify inpatient progress notes describing falls | Mathematical/text data | NA | Natural language processing was highly specific (0.97) but had low sensitivity (0.44) in identifying fall risk compared to manual records review |
| Songur and Top [58] | To analyze clusters from 12 regions in Turkey in terms of medical imaging technologies' capacity and use | Mathematical/text and numerical data | NA | The study identified inequities in medical imaging technologies according to regions in Turkey and hospital ownership |
| Swangnetr and Kaber [59] | To develop an efficient patient-emotional classification computational algorithm in interaction with nursing robots in medical care | Survey study: self-assessment manikin questionnaire to measure emotional response to the robot | 24 residents | Wavelet-based denoising of galvanic skin response signals led to an increase in the percentage of correct classifications of emotional states, and more transparent relationships among physiological responses and arousal and valence |
| Wagland et al [60] | To analyze the patient experience of care and its effect on health-related quality of life | Survey study regarding treatment, disease status, physical activity, functional assessment of cancer therapy, and social difficulties inventory | NA | Nearly half of the total comments analyzed described positive care experiences. Most negative experiences concerned a lack of posttreatment care and insufficient information concerning self-management strategies or treatment side effects |
| Wang et al [61] | To evaluate a population health intervention to increase anticoagulation use in high-risk patients with atrial fibrillation | Mathematical/text and numerical data | NA (data from 14 primary care clinics) | After pharmacist review, only 17% of algorithm-identified patients were considered potentially undertreated |
| Waqar et al [62] | To analyze patients' interest in selecting a doctor | Survey study: systems evaluation from patients' and doctors' perspectives | NA (data from 3 hospitals) | The proposed system solved the problem of doctor recommendations to a good effect when evaluated by domain experts |
| Xiao et al [63] | To achieve personalized identification of cruciate ligament and soft tissue insertions and, consequently, capture the relationship between the spatial arrangement of soft tissue insertions and patient-specific features extracted from the tibia outlines | Mathematical/image data | 20 patients | The supervised learning and prediction method developed in this study provided accurate information on soft tissue insertion sites using the tibia outlines |
| Valik et al [64] | To develop and validate an automated Sepsis-3-based surveillance system in a nonintensive care unit | Mathematical/text and numerical data | NA | The Sepsis-3 clinical criteria determined by physician review were met in 343 of 1000 instances |
| Bailey et al [65] | To study the implementation of a clinical decision support system (CDSS) for acute kidney injury | Interview and observation study: organizational work of technology adoption | 49 clinicians | Hospitals faced difficulties in translating the CDSS's recommendations into routine proactive output |
| Carayon et al [66] | To improve the usability of a CDSS | Experimental study: simulation and observation to evaluate the usability | 32 clinicians | Emergency physicians faced lower workload and higher satisfaction with the human factors-based CDSS compared to the traditional web-based CDSS |

| Study | Objective | Methods and Data | Study participants | Immediate outcome observed |
|-----------------------|--|--|---|--|
| Parekh et al [67] | To develop and validate a risk prediction tool for medication-related harm in older adults | Mathematical/numerical data | 1280 elderly patients | The tool used eight variables (age, gender, antiplatelet drug, sodium level, antidiabetic drug, past adverse drug reaction, number of medicines, living alone) to predict harm with a C-statistic of 0.69 |
| Gilbank et al [68] | To understand the needs of the user and design requirements for a risk prediction tool | Survey and interview study: informal, semistructured meetings | 15 stakeholders from hospitals, academia, industry, and nonprofit organizations | Nine physicians emphasized the need for a prerequisite for trusting the tool. Many participants preferred the technology to have roles complementary to their expertise rather than to perform tasks the physicians had been trained for. Having a tailored recommendation for a local context was deemed critical |
| Miller et al [69] | To understand the usability, acceptability, and utility of AI-based symptom assessment and advice technology | Survey study to measure ease of use | 523 patients | 425 patients reported that using the Ada symptom checker would not have made a difference in their care-seeking behavior. Most patients found the system easy to use and would recommend it to others |
| ter Stal et al [70] | To analyze the impact of an embodied conversational agent's appearance on user perception | Interview study: Acosta and Ward Scale [71] | 20 patients | The older male conversational agent was perceived as more authoritative than the young female agent ($P=.03$). Participants did not see an added value of the agent to the health app |
| Gabrielli et al [72] | To evaluate an online chatbot and promote the mental well-being of adolescents | Experimental, participatory design, and survey study to measure satisfaction | 20 children | Sixteen children found the chatbot useful and 19 found it easy to use |
| Liang et al [73] | To develop a smartphone camera for self-diagnosing oral health | Interview Study to measure usability (NASA-TLX) | 500 volunteers | Two experts agreed that OralCam could give acceptable results. The app also increased oral health knowledge among users |
| Chatterjee et al [74] | To assess the feasibility of a mobile sensor-based system that can measure the severity of pulmonary obstruction | Mathematical/numerical data | 91 patients, 40 healthy participants | Most patients liked using a smartphone as the assessment tool; they found it comfortable (mean rating 4.63 out of 5 with $\sigma=0.73$) |
| Beede et al [75] | To evaluate a deep learning-based eye-screening system from a human-centered perspective | Observation and interview study: unstructured | 13 clinicians, 50 patients | Nurses faced challenges using the deep-learning system within clinical care as it would add to their workload. Low image quality and internet speed hindered the performance of the AI system |

^aNA: not applicable; these studies have only used data for their respective analyses without involving any human participant (user).

^bEHR: electronic health record.

^cAI: artificial intelligence.

We observed various algorithms in the final selection, with machine learning being the most common ($n=18$). Some studies also compared different algorithms based on analytical performance. However, few studies ($n=5$ against clinical/baseline standards, $n=5$ against clinicians) compared their AI models against a standard measure.

Table 2 summarizes the studies that used machine-learning algorithms. These studies emphasized algorithm development without considering human factors in substantial depth. In other

words, the technological focus of many studies is currently on human-AI collaboration in health care while neglecting real-life clinical evaluation. Discussing studies that primarily focused on analytical performance is beyond the scope of this review. The general flaws and trends of such studies have been addressed in our prior work [7].

Overall, our review indicates that the dimensions of usability, user's perception, workload, and trust in AI have been the most common interest of research in this field.

Table 2. Artificial intelligence (AI) studies that primarily focused on machine learning (ML) algorithm development (n=18).

| Reference | AI/ML recommended by the study | Other AI/ML/non-AI used in the study | Proposed AI model(s) for comparison (1=compared; 0=not compared) | | | |
|------------------------------|--|--|--|--------------------------|---------------------------|--------------------|
| | | | Other AI systems | Existing system (not AI) | Clinical or gold standard | Clinicians or user |
| Aldape-Pérez et al [24] | Delta Associative Memory | AdaBoostM1; bagging; Bayes Net; Dagging; decision table naïve approach; functional tree; logistic model trees; logistic regression; naïve Bayes; random committee; random forest random subspace; Gaussian radial basis function network; rotation forest; simple logistic; support vector machine | 1 | 0 | 0 | 0 |
| Azari et al [25] | Random forest and hidden Markov model | Not applicable | 1 | 1 | 1 | 0 |
| Balani and De Choudhury [26] | Perceptron | Naïve Bayes; k-nearest neighbor; decision tree | 1 | 0 | 0 | 0 |
| Cvetković and Cvetković [28] | Neural network and fuzzy logic | Not applicable | 0 | 0 | 0 | 0 |
| Gao et al [34] | AdaBoost | k-nearest neighbor, support vector machine, decision tree, random forest, naïve Bayes | 1 | 1 | 1 | 0 |
| Hu et al [36] | Deep neural network | Deep neural network with different inputs | 1 | 0 | 0 | 0 |
| Kandaswamy et al [38] | Random forest | Naïve Bayes; logistic regression; support vector machine | 1 | 0 | 0 | 0 |
| Komogortsev and Holland [39] | Supervised support vector machine | Unsupervised support vector machine and unsupervised heuristic algorithm developed by the authors | 1 | 0 | 0 | 0 |
| Marella et al [44] | Naïve Bayes kernel | Naïve Bayes; k-nearest neighbor; rule induction | 1 | 0 | 0 | 1 |
| Nobles et al [50] | Deep neural network | Support vector machine | 1 | 0 | 0 | 0 |
| Ong et al [51] | Naïve Bayes; support vector machine with radial-bias function | Support vector machine with a linear function | 1 | 1 | 1 | 1 |
| Shiner et al [57] | Natural language processing | Incident reporting system; manual record review | 1 | 1 | 1 | 1 |
| Wagland et al [60] | Did not recommend any particular algorithm | Support vector machine; random forest; decision trees; generalized linear models network; bagging; max-entropy; logi-boost | 1 | 0 | 0 | 0 |
| Waqar et al [62] | Hybrid algorithm developed by the authors | Not applicable | 0 | 0 | 0 | 0 |
| Xiao et al [63] | The authors developed a new algorithm | Linear regression with regularization; LASO ^a ; k-nearest neighbor; population mean | 1 | 0 | 0 | 0 |
| Valik et al [64] | The authors developed a new algorithm | Not applicable | 0 | 0 | 1 | 1 |
| Parekh et al [67] | The authors developed an algorithm based on multi-variable logistic regression | Not applicable | 0 | 1 | 0 | 0 |
| Chatterjee et al [74] | Gradient boosted tree | Random forest, adaptive boosting | 0 | 0 | 0 | 1 |

^aLASSO: least absolute shrinkage and selection operator.

Perception, Usability, Workload, and Trust

Perception

The perception of users was analyzed by several studies to adequately assess the quality of the proposed AI-based

recommender system. Some studies incorporated perceptions of both patients and doctors [62,73] in developing their AI systems. Another study interviewed providers (therapists) about their experiences, opinions, expectations, and perceptions of a motion-based game for brain injury rehabilitation to guide the

design of the proposed AI-based recommender system, which was a case-based reasoning (CBR) system [55]. The AI system ASSESS MS was also developed and evaluated based on users' perceptions [48]. Studies included in our review that developed AI-based apps [27,29], AI robots [30], and wearable AI devices such as Gait Assist [45] and Itchtector [43] also accounted for users' perceptions. From a psychological perspective, emotions might facilitate perception [76]. One study in our review measured users' perception of an AI-based conversational agent [70], and another study developed an AI algorithm for real-time detection of patient emotional states and behavior adaptation to encourage positive health care experiences [59].

Usability

Some studies in our review performed usability testing of AI systems. For example, one study used AI to develop an adaptable CBR to help therapists ensure proper usability and functioning of CBR [55]. Guided by users' needs, one study [27] developed an AI application (SMILY) to ensure good usability. Users found the clinical information to have higher diagnostic utility while using SMILY (mean 4.7) than while using the conventional interface (mean 3.7). They also experienced less effort (mean 2.8) and expressed higher trust (mean 6) in SMILY than with the conventional interface (mean 4.7; $P=.01$), as well as higher benevolence (mean 5.8 vs 2.6; $P<.001$). Another study included in our review noted the literacy gap as a significant hurdle in the usability of an AI-based face-reading app, and identified the impact of adaptability and cultural sensitivity as a limiting factor for usability [29]. Another study codesigned an AI chatbot with 20 students and performed a formative evaluation to better understand their experience of using the tool [72]. Two recent studies measured the perceived usability of AI-based decision-making tools: Ada, an AI tool that helps patients navigate the right type of care [69], and PE-Dx CDS, a tool for diagnosing pulmonary embolism [66]. However, in another study, the researchers primarily focused on developing the algorithm for assessing the severity of pulmonary obstruction and obtained users' feedback on the end product [74]. Poor usability often leads to an increased workload, particularly when the user (provider or patient) is not trained in using the AI system, device, or app.

Workload

Caregivers are subject to workplace stress and cognitive workload, mostly due to the complexities and uncertainty of patient health and related treatment [77-79], and AI promises to minimize the health care workload through the automation of various levels. Nevertheless, if an AI system or program is poorly designed, the workload may possibly be elevated. Two studies in our review used a radial basis function network to assess burnout among nurses, and consequently captured the nonlinear relationship of the burnout process with the workload, work experience, conflictive interaction, role ambiguity, and other stressors [41,42]. The demand-control theory of work stress implies that workload abnormalities and job intensity can aggravate user fatigue by excessive workloads and trigger anxiety [80]. According to Maslach and Leiter [81], a mismatch between one's skill sets (ability to perform a task) and responsibility (skills required to complete a task) intensifies

users' workload. Three studies in our review were invested in minimizing users' workload by assessing the usability of AI systems such as ASSESS MS [48], Gait Assist [45], and SMILY [27].

Trust

Trust shapes clinicians' and patients' use, adoption, and acceptance of AI [6]. Trust is a psychological phenomenon that supports the inconsistency between the known (clinicians' awareness, patient experience) and the unknown (deep-learning algorithms). Three studies included in our review measured user trust in health care AI systems. One study reported that the anthropomorphism of AI-based care robots has no influence on providers' trust but was significantly related to the level of automation and intention to work with the robot [30]. This study proposed that providers who trusted robots more intended to work with them and preferred a higher automation level [30]. A recent perspective discusses the risk of overreliance or maximum trust in AI (automation) and instead suggests optimal trust between the user and AI system [6]. Besides experience, expertise, and prior knowledge, the performance of the AI technology also determines users' trust. A study included in our review, using a poststudy questionnaire, found that doctors (pathologists) expressed higher trust in SMILY, an AI-based application, due to its better performance, interface, and higher benevolence compared with the conventional app [27]. By contrast, another study reported lower trust of experienced physicians in an AI-based recommendation tool due to its inefficient performance [54]. Based on patient data, expert physicians were able to identify the alternative and better explanation for patient health compared to the AI-based tool [54]. A recent study identified the impact of the AI interface on user's trust [68]. Physicians in this study considered AI's transparency and performance as facilitators of engendering trust.

User-Centered Design

A user-centric design requires multidisciplinary cooperation between HFE experts, technologists, and end users. The inadequacy of a user-centered design also hinders user perception, usability, and trust, and increases the possibility of errors. The majority of the health care AI literature focuses on quantitative constraints, including performance metrics and precision, and is less focused on the user-centric development of AI technologies. Due to the lack of standard guidelines [7,16], not much research has invested in incorporating a user-centered design in AI-based technologies within the health care industry. In this review, we identified studies that performed experiments involving clinicians and patients, and consecutively evaluated their AI system's (eg, app, wearable device) interface [27], applicability [27,29], and appearance (anthropomorphism) [30] to ensure user-centeredness. Other studies [43,45,48,49,55,62] also addressed user requirements such as wearability and privacy concerns. A recent study further acknowledged the importance of a user-centered clinical field study, and identified external factors such as low lighting, expensive image annotation, and internet speed that can deter the effectiveness of AI systems for diagnosing diabetic retinopathy [75].

Discussion

Main Findings

Research concerning AI in health care has shown promise for augmenting the quality of health care. However, there is a need for more theoretical advances and interventions that cover all levels and operations across the health care system. We need a systematic approach to safely and effectively bring AI into use, providing human factors, user-centered design, and delivery and implementation science. Many current AI models focus on engineering technology (informatics concepts) and do not sufficiently discuss the relevance of HFE in health care [82]. In this review, we explored and portrayed the involvement of HFE journals and conferences in health care AI research. We identified 48 studies, trending as more publications in recent years, which shows increased attention of the HFE community in this field.

Although advancement and focus have been made in the use of machine learning/AI to develop prediction and classification models, little research has been devoted to real-world translations with a user-centered design approach. To determine the diverse relationships between individuals and technology within a work environment, it is necessary to provide a better explanation as to how AI can be part of the overall health care system through a variety of HFE methods such as the Systems Engineering Initiative for Patient Safety (SEIPS) [83]. The SEIPS provides a framework that helps in comprehending the work system (people, tools and technologies, tasks, working environment, and organization), process (clinical process and process assisting the same), and outcomes (patient outcome, organizational outcome) in the health care domain [83]. This framework also helps to assess and understand the complex interaction between elements of the work system, and shows the impact of any technology-based intervention on the overall system [83].

This review also highlights the need for a systematic approach that evaluates AI's impact (effectiveness) on patient care based on its computational capabilities and compatibility with clinical workflow and usability. Although some studies have acknowledged AI's challenges from both human factors (biases and usability) [84] and technical (quality of training data and standardization of AI) [7] standpoints, less emphasis has been given so far to the impact of AI integration into clinical processes [16] and services as well as to the user-centered design of AI systems for better human-AI interaction [84,85]. At this stage, where human beings and AI come together, challenges to human factors will likely arise.

Next Steps

The next push for researchers should be to move AI research beyond solely model development into sociotechnical systems research and effectively use human factors principles. HFE researchers should consider users' needs, capabilities, and interactions with other elements of the work system to ensure the positive impact of AI in transforming health care. Clinical systems are not inherently equivalent to predictable mechanical systems and need a systematic approach. One of the pivotal myths of automation is the assumption that AI can replace

clinicians [33]. In fact, the use of AI can shape the activities and duties of clinicians, and might help them in their decision-making. In the domain of medical imaging, AI has shown great promise and is increasing rapidly. For instance, on January 18, 2021, an image analysis platform named AI Metrics received US Food and Drug Administration (FDA) 510(k) clearance [86]. Likewise, in the last 5 years, approximately 222 AI-based medical devices have been approved in the United States [87]. As AI continues to grow, the associated risks also increase. Many health care AI systems are poorly designed and not evaluated thoroughly [14], and have neglected clinicians' limited absorptive and cognitive capacities and their ability to use AI in clinical settings under a high cognitive workload [88-90]. Incorrect usage or misinterpretation of AI, similar to that of EHRs [91], may also result in patient harm. Therefore, more HFE research should focus on cognitive factors (biases, perceptions, trust), usability, situation awareness, and methodological aspects of AI systems.

Usability

A user-centered design is essential for health care technologies, where the user is centrally involved in all phases of the design process [92]. However, when the user environment and activities are varied, designing standardized protocols for health care devices and software is complicated. As stated in this study, the problem further increases due to the heterogeneity of applications and AI variants. The human-computer interaction community has developed different user-centered design techniques. However, these methods are often underused by software development teams and organizations [93].

Usually, AI algorithms are complex, opaque, and thus difficult to understand. Therefore, it might be difficult for clinicians/end users to understand and interpret AI outcomes effectively without adequate instruction. Cognitive ergonomics is a fundamental principle dealing with usability issues [94]. Necessary procedural information stored in long-term memory is required to use a technical device [95]. Kieras and Polson [95] suggested the cognitive complexity theory (CCT) explicitly addressing the cognitive complexity of the user-to-device/interface interaction by explaining the user's goals on the one hand and the computer system reaction on the other hand using production rules. The laws of production can be viewed as a series of rules in the form of IF conditions (display status) and THEN actions (input or action taken by the user). According to CCT, cognitive complexity is defined as the number of production rules segregated and learned in a specific action sequence. The definition of cognitive complexity in an AI-based health app can be as helpful as the definition of production rules (ie, the specification of what the system says and how users react) and factors that may contribute concurrently to the app's complexity (ie, interface, menu structure, the language of communication, transparency of functions' naming). It is, however, debatable whether the mere counting of production rules will reasonably assess the troubles perceived by users, considering that various factors contribute equitably to cognitive complexity. Cognitive computing systems [96], which are computing systems that can incorporate human-like cognitive abilities, can also augment and safeguard health care AI by making AI *adaptive* (learning from a changing

environment, changing patient health, changing clinician's requirements), interactive (easier human-AI interaction, better usability, easy to understand), iterative and stateful (narrowing down on the problem, considering past decisions/consequence while making current recommendations/tasks), and contextual (consider contextual elements) [96].

Moreover, challenges and hardships perceived by users might be a function of several factors not limited to the user's experience, knowledge, intention of use, and working environment [97]. Therefore, an adaptable usability scale that encompasses the complexity of AI and the common usability factors applicable to that particular system or software should be created by HFE researchers. Perception of an AI system or its perceived ease of use can potentially be a function of users' cognitive and physical abilities. Additionally, the obvious question is, where should user-centered design techniques and knowledge be considered in the life cycle of AI's development?

Trust and Biases

Human factors research on "automation surprises" primarily began with large-scale industrialization that involved autonomous technologies [84,98,99]. The automation surprise arises when an automated machine acts counterintuitively [100]. In health care, automation surprises might lead to confusion, higher workload, distrust, and inefficient operations [101]. In the health care environment, inadequate mental models and insufficient information about AI-based technology might lead to automation surprises and negatively influence trust [6]. Trust can also be hindered if an automated system tends to deter clinicians' performance [6]. Research evaluating the performance of radiologists observed their deterring performance when aided by a decision support system [102]. Therefore, more HFE studies are needed that explore the factors and design requirements influencing users' and clinicians' optimal trust in AI. Future studies should also focus on patient trust in AI-generated recommendations.

When automated diagnostic systems are used in real-life clinics, they most likely are in the form of assistant or recommender systems where the AI system provides information to clinicians or patients as a second opinion. However, if the suggestions made by AI are entirely data-driven without accounting for the user's opinion, as is the case for current designs, users could be biased toward or against the suggestion of the AI system [103]. Optimizing such user-AI trust interplay remains a challenge that HFE experts should consider as their future endeavor.

It should be noted that advocating for trust in automation for a prolonged time can also promote automation bias. Aviation studies have recorded instances of automation biases where pilots could not track vital flight indicators in the event of failure due to overreliance on the autopilot [104,105]. A review of automation bias focusing on the health care literature noted that the complexity of any assignment and the workload increased the likelihood of excessive reliance on automation [106], which can be detrimental to patient safety. Human factors such as cognitive ergonomics and a user-centered design should be utilized efficiently to minimize the health care AI system's automation biases.

Situation Awareness

Situation awareness is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future" [107]. "Good" situation awareness is a prerequisite to better performance [84,107]. There might be an ongoing discussion around maximum versus optimum situation awareness. It is critical to understand that the optimum situation awareness is not necessarily the maximum situation awareness [108]. Maximizing the user's situation awareness does not necessarily yield the best outcome (decisions from a human-AI collaboration) [108]. For example, concentrating on irrelevant details such as radio commercials, talking passengers, or the colors of other cars while driving may unnecessarily consume the driver's working memory, increase the workload, or even act as a distraction [109].

Similarly, in a clinical setting, it is better to achieve optimal situation awareness rather than maximum situation awareness. Many studies have shown the deterring impact of excessive and unnecessary information on clinical work [110,111]. For example, false or irrelevant clinical alarms may increase the tension of nurses and even distract them. Performing critical health care tasks (such as administering narcotic medication, watching telemetry monitors) demands optimal situation awareness [112]; however, unnecessary or irrelevant situation awareness can disturb clinicians' attention and working memory. Exploration of AI's influence on clinicians' situation awareness has not been studied extensively. More HFE-based research is needed to further explain the concept of optimal situation awareness in AI design. Both humans and AI each have skepticism regarding the information generated in their surroundings and extract the data that seem vital for clinical decision-making.

Ecological Validation

The development, evaluation, and integration of sophisticated AI-based medical devices can be a challenging process requiring multidisciplinary engagement. It may enable a personalized approach to patient care through improved diagnosis and prognosis of individual responses to therapies, along with efficient comprehension of health databases. This solution has the power to reinvent clinical practices. Although the advent of personalized patient treatment is provocative, there is a need to evaluate the true potential of AI. The performance of AI depends on the quantity and quality of data available for training, as acknowledged in recent review papers [7,16]. Perhaps one of the most essential facts from the HFE viewpoint is that poor usability causes improper, inaccurate, and inefficient use [113]. Although the importance of usability testing and a user-centered design for medical devices has been substantially stated by the FDA [114] and other HFE experts, both regulatory guidelines and evaluation approaches fail to reflect the challenges faced by clinicians during their routine clinical activity [115]. In other words, most studies identified in our review were performed in a controlled environment, therefore lacking ecological validity. This finding is consistent with most other research in the field of AI and health care. Recent systematic reviews [7,16,116] analyzing AI's role and performance in health care

acknowledged that AI systems or models were often evaluated under unrealistic conditions that had minimal relevance to routine clinical practice.

Users under stress and discomfort might not be efficient in utilizing AI devices with poor usability. Unlike research or controlled settings, a clinical setting demands multitasking where clinicians (nurses) have to attend to several patients with different ailments. They also have to write clinical notes, monitor health fluctuations, administer critical medications, float to different departments during shortage of staff, educate new nurses, and respond to protocols in cases of emergency. Under such a working environment and cognitive workload, interpreting or learning to use an AI system that is not designed appropriately can be challenging and risky. Therefore, an AI system that perfectly qualifies usability tests in a research setting may fail in a clinical environment. Given these limitations, the few studies in our review that compared their AI model with clinical standards (see [Table 2](#)) are less relevant because the comparisons against clinical standards were made in an (ideal) controlled environment or without providing contextual information about the patient and the environment [117]. Moreover, the work system elements also differ substantially from an intensive care unit to an outpatient clinic. Therefore, AI-based medical systems must be evaluated in their respective clinical environment to ensure safer deployment.

Limitations of the Review

This review does not include the complete available literature but was constrained within the selected journals and conferences. Studies investigating human-AI interactions in a health care context or leveraging HFE principles to evaluate health care AI systems published in non-HFE venues such as pure medical or informatics journals have not been included in this review. Notwithstanding these constraints, our analysis identified possible research gaps in the health disciplines that could, if addressed, help mobilize and integrate AI more efficiently and safely.

Conclusion

HFE researchers should actively design and implement AI, and perform dynamical assessments of AI systems' effects on interaction, workflow, and patient outcomes. An AI system is part of a greater sociotechnical system. Investigators with HFE expertise are essential when defining the dynamic interaction of AI within each element, process, and result of the work system. This means that we ought to adapt our strategy to the situations and contexts in the field; simultaneously, we must also find practical ways of generating more compelling evidence for our research.

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Authors' Contributions

OA conceived and designed the study; developed the protocol; participated in data collection (literature review), analysis, and interpretation; drafted and revised the manuscript; and approved the final version for submission. AC designed the study; developed the review protocol and graphical illustrations; participated in the literature review, analysis, and interpretation; drafted and revised the manuscript; and approved the final version for submission.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Journal and conference proceedings list for the review.

[[DOCX File, 19 KB - humanfactors_v8i2e28236_app1.docx](#)]

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Abbreviations

- AI:** artificial intelligence
- CBR:** case-based reasoning
- CCT:** cognitive complexity theory
- EHR:** electronic health record
- FDA:** Food and Drug Administration
- HFE:** human factors and ergonomics
- SEIPS:** Systems Engineering Initiative for Patient Safety

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Original Paper

Impact of an Educational Comic to Enhance Patient-Physician–Electronic Health Record Engagement: Prospective Observational Study

Maria A Alkureishi^{1*}, MD; Tyrone Johnson^{2*}, MD; Jacqueline Nichols^{3*}, MD; Meera Dhodapkar^{4*}, BS; M K Czerwicz^{5*}, RN; Kristen Wroblewski^{6*}, MS; Vineet M Arora^{7*}, MD, MAPP; Wei Wei Lee^{7*}, MD, MPH

¹Department of Academic Pediatrics, University of Chicago, Chicago, IL, United States

²Department of Internal Medicine, University of California, San Francisco, San Francisco, CA, United States

³Department of Obstetrics and Gynecology, University of Washington, Seattle, WA, United States

⁴Yale University School of Medicine, New Haven, CT, United States

⁵Center for Medical Humanities & Bioethics, Feinberg School of Medicine, Northwestern University, Chicago, IL, United States

⁶Department of Public Health Sciences, University of Chicago, Chicago, IL, United States

⁷Department of Medicine, University of Chicago, Chicago, IL, United States

* all authors contributed equally

Corresponding Author:

Maria A Alkureishi, MD

Department of Academic Pediatrics

University of Chicago

5841 S Maryland Ave

MC 6082 Rm C124

Chicago, IL, 60637

United States

Phone: 1 773 834 8927

Email: malkureishi@peds.bsd.uchicago.edu

Abstract

Background: Electronic health record (EHR) use can impede or augment patient-physician communication. However, little research explores the use of an educational comic to improve patient-physician-EHR interactions.

Objective: To evaluate the impact of an educational comic on patient EHR self-advocacy behaviors to promote patient engagement with the EHR during clinic visits.

Methods: We conducted a prospective observational study with adult patients and parents of pediatric patients at the University of Chicago General Internal Medicine (GIM) and Pediatric Primary Care (PPC) clinics. We developed an educational comic highlighting EHR self-advocacy behaviors and distributed it to study participants during check-in for their primary care visits between May 2017 and May 2018. Participants completed a survey immediately after their visit, which included a question on whether they would be interested in a follow-up telephone interview. Of those who expressed interest, 50 participants each from the adult and pediatric parent cohorts were selected at random for follow-up telephone interviews 8 months (range 3-12 months) post visit.

Results: Overall, 71.0% (115/162) of adult patients and 71.6% (224/313) of pediatric parents agreed the comic encouraged EHR involvement. African American and Hispanic participants were more likely to ask to see the screen and become involved in EHR use due to the comic (adult $P=.01$, $P=.01$; parent $P=.02$, $P=.006$, respectively). Lower educational attainment was associated with an increase in parents asking to see the screen and to be involved ($\rho=-0.18$, $P=.003$; $\rho=-0.19$, $P<.001$, respectively) and in adults calling for physician attention ($\rho=-0.17$, $P=.04$), which was confirmed in multivariate analyses. Female GIM patients were more likely than males to ask to be involved (median 4 vs 3, $P=.003$). During follow-up phone interviews, 90% (45/50) of adult patients and all pediatric parents (50/50) remembered the comic. Almost half of all participants (GIM 23/50, 46%; PPC 21/50, 42%) recalled at least one best-practice behavior. At subsequent visits, adult patients reported increases in asking to see the screen (median 3 vs 4, $P=.006$), and pediatric parents reported increases in asking to see the screen and calling for physician attention (median 3 vs 4, $P<.001$ for both). Pediatric parents also felt that the comic had encouraged them to speak up and get

more involved with physician computer use since the index visit (median 4 vs 4, $P=.02$) and that it made them feel more empowered to get involved with computer use at future visits (median 3 vs 4, $P<.001$).

Conclusions: Our study found that an educational comic may improve patient advocacy for enhanced patient-physician-EHR engagement, with higher impacts on African American and Hispanic patients and patients with low educational attainment.

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KEYWORDS

electronic health records; patient; comic; education; engagement

Introduction

Electronic health record (EHR) use in clinical care has become the norm in the United States [1-3]. Studies on the impact of EHR use have found that certain physician behaviors (eg, poor eye contact, long silences) may lead to decreased patient satisfaction with the patient-physician relationship and communication [4-11]. While studies show there are certain patient-centered care behaviors that can positively impact patient satisfaction and health outcomes, with Table 1 serving as a model for incorporating many evidence-based behaviors, physicians are faced with the challenge of staying focused on their patients while efficiently navigating the EHR during clinical encounters [4,6,12-20].

In a 2016 study on patient perceptions of physician EHR use in an academic primary care practice, patients were dissatisfied when physicians appeared more focused on the computer than on them and frustrated with lack of transparency and poor body positioning, which contributed to perceptions of decreased

quality of care [7]. While best practices to promote patient-centered EHR use have been identified, most physicians and patients are unaware of these strategies to improve patient-physician-EHR communication [6,12,20-26].

Educational comics have emerged as an innovative way to promote patient education and engagement in a variety of clinical settings including pediatric, gynecology, radiation oncology, neurology, and endocrine practices [27-34]. Despite these findings, to our knowledge, no studies have looked at using educational comics to promote patient-centered EHR use in academic primary care practices. Furthermore, prior studies have found that Black and Hispanic patients and those with lower educational attainment level experience increased health care disparities, which in turn may result in poorer health outcomes [35-47]. As such, we aim to assess the impact of an educational comic on patient self-advocacy behaviors to enhance patient engagement with the EHR and to determine if there are variable impacts of the comic on different patient demographic variables such as ethnicity and education attainment level.

Table 1. HUMAN LEVEL—10 tips to enhance patient-centered electronic health record use [20].

| Initial | Tip | Description |
|---------|------------------------------|---|
| H | Honor the “Golden Minute” | Make the start of the visit completely <i>technology-free</i> . Greet the patient, start with <i>their</i> concerns, and establish an <i>agenda</i> for the visit <i>before</i> engaging technology. |
| U | Use the “Triangle of Trust” | Create a <i>triangle configuration</i> that puts you, the patient, and the computer screen at each of the three corners. This allows you to look at both the patient and screen without shifting your body position, and also enables <i>shared</i> screen viewing. |
| M | Maximize patient interaction | Encourage patient <i>interaction</i> . Pause for questions and clarification. Allow time for questions and to verify understanding. |
| A | Acquaint yourself with chart | Review the chart <i>before</i> you enter the room to prepare, inform, and <i>contextualize</i> your visit. |
| N | Nix the screen | When discussing <i>sensitive</i> information, <i>completely disengage</i> from the EHR ^a (look at the patient, turn away from screen, take hands off keyboard, etc). |
| L | Let the patient look on | <i>Share</i> things on the screen with your patients. |
| E | Eye contact | Maintain <i>eye contact</i> with patients as much as possible. Treat patient encounters as you would a conversation with friends or family members. |
| V | Value the computer | Praise the <i>benefits</i> of the EHR and take advantage of opportunities to use technology as a tool to <i>engage</i> patients (pull up lab result to review together, utilize graphics, etc). |
| E | Explain what you’re doing | Be <i>transparent</i> about everything you do. Avoid long silences, aim for conversational EHR use by explaining what you are doing as you are doing it. |
| L | Log off | At the end of the visit, <i>log off</i> of the patient’s chart while they are still in the exam room. This reassures patients that their medical information is <i>secure</i> . |

^aEHR: electronic health record.

Methods

Setting and Participants

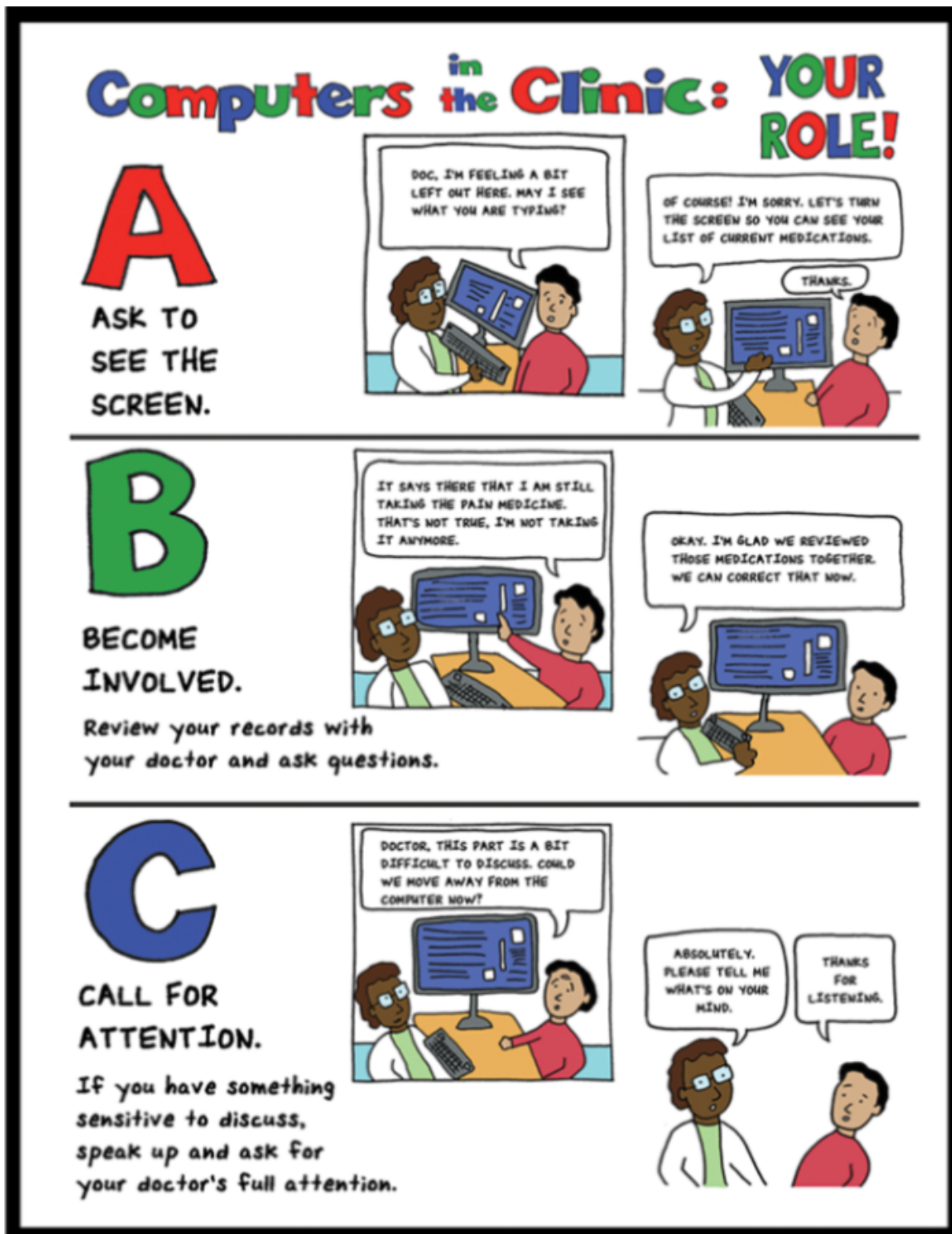
The study was conducted at the University of Chicago's General Internal Medicine (GIM) and Pediatric Primary Care (PPC) clinics between May 2017 and May 2018. Adult GIM patients and pediatric parents who were scheduled to see faculty physicians were approached by trained research assistants in the waiting room and verbally consented to participate in the study. Inclusion criteria included ability to consent and English proficiency. GIM and PPC faculty physicians were given information about the study at their respective section meetings and via email communications, and all consented to having their patients participate. Of note, the ergonomic room layout in both clinics is such that the screen is usually not easily viewed by

the patient unless it or the chairs in the room are moved to encourage shared viewing.

Comic Development

The educational comic (Figure 1), "Computers in the Clinic: Your Role," was developed by the authors (MAA, WWL, VMA, MKC) based on a literature review of the impact of EHR use on patient-physician communication [4-6,8,9]. The comic was drawn by author MKC, a practicing nurse with experience in designing educational comics for patient education interventions. It highlights three patient self-advocacy behaviors aimed at improving patient EHR engagement: (1) A for "Ask to see the screen" to promote screen sharing, (2) B for "Become involved with your doctor's use of the computer" to encourage patient-physician-EHR interaction and patient education, and (3) C for "Call for attention" to encourage patients to speak up if they feel their physician is distracted by the EHR.

Figure 1. Patient EHR self-advocacy comic. The educational comic was given to adult patients and parents of pediatric patients when registering for their clinic visits to encourage EHR self-advocacy behaviors and engagement. EHR: electronic health record. © Alkureishi ML, Czerwicz MK, Arora V, Lee WW and the Arnold P. Gold Foundation.



Postvisit Survey and Telephone Interview Script Development

Using findings from a literature review, a 33-item postvisit survey was developed containing open-ended and Likert scale questions to assess the comic's impact on patient (1) self-advocacy behaviors for more engaging and meaningful

patient-physician-EHR interactions, (2) satisfaction with physician EHR use, and (3) perceptions of physician communication at the current visit compared to patient recollections of communication with the same provider at prior visits [4-6,8,9] (Multimedia Appendix 1). Studies have shown that patient self-report is a reasonable method of assessing whether educational interventions improve subsequent behaviors

and self-advocacy [48-52]. Furthermore, we wanted to directly ask patients what they thought about the patient-physician-EHR interaction and impacts of the comic on their behavior and perceptions, rather than use an observer or their clinician's perceptions as an indirect proxy.

A semistructured telephone interview script was developed to assess (1) patient recall of the comic and (2) impact of the comic on patient perceptions and self-advocacy behaviors and EHR engagement at subsequent physician visits ([Multimedia Appendix 2](#)). The interview script contained 6 5-point Likert-style questions to assess patient perceptions of the comic and impact on behaviors since the index visit (eg, "The comic encouraged me to speak up and get more involved with the computer at my subsequent visits with my doctor.") as well as open-ended questions to prompt patient responses (eg, "Can you give me some examples of how you've asked to get more involved with your doctor's use of the computer during clinic visits?").

Intervention

The hypothesis for our study was that more than 50% of respondents would agree that the comic made them get more involved with the computer (null hypothesis: $\rho=50\%$ vs alternative hypothesis: $\rho>50\%$). Our calculations assumed 80% power and one-sided exact binomial test with $\alpha=.025$. Based on this, we found that a sample size of 200 in each group would be sufficient to reject the null hypothesis if the true rate was 60%, which is why we estimated a total of 400-500 postvisit surveys in total would be needed to assess our outcomes. This sample size estimation was consistent with prior telephone interview studies at the University of Chicago with the same patient population and similar survey and interview techniques [7,53].

Adult GIM patients and pediatric parents who consented to the study were given the educational comic and a postvisit survey. Participants were instructed to (1) review the comic while waiting for their appointment and (2) complete the survey at the end of their visit. The postvisit survey included a question on whether participants would be interested in participating in a follow-up telephone interview at a mean of 8 months (range 3-12 months) after their clinic visit. Of those who expressed interest, 50 participants each from the adult and pediatric parent cohorts were selected at random for the interviews, which were conducted between July 2017 and October 2018. Participants orally consented to participate in the phone interview ([Multimedia Appendix 2](#)). A US \$20 gift card was offered as compensation for their time. Phone interviews were digitally recorded and transcribed to ensure accuracy.

Data Analysis

Descriptive statistics of patient postvisit surveys and phone interview responses were examined. Standard descriptive statistics were calculated including frequency counts and percentages, mean (standard deviation), or median. Univariate

analyses were initially performed; since survey responses were on an ordinal Likert scale, nonparametric tests were used. Comparisons of survey responses involving three or more groups (eg, race) were made using Kruskal-Wallis tests, while comparisons involving two groups (eg, gender) were made using Wilcoxon rank sum tests. Associations between educational attainment and survey responses were examined using Spearman rank correlation coefficients. Pairwise comparisons were completed using Tukey's honestly significant difference test. Phone survey versus postvisit survey response comparisons were completed using the Wilcoxon signed rank test for matched pairs. Multivariate analyses looking at whether gender, race, and education were independently associated with the odds of agreeing with a particular survey question (eg, "agree" was defined as a Likert response ≥ 4) were performed using logistic regression. Analysis was performed using Stata 14 (StataCorp LP, College Station, Texas). No adjustment for multiple testing was made. Our paper conforms to the SQUIRE 2.0 Revised Standards for Quality Improvement Reporting Excellence [54]. This study was approved by the University of Chicago's Institutional Review Board.

Results

Overview

The study enrollment rate was 83.5% (197 consented/236 approached) for adult patients and 77.9% (325 consented/417 approached) for the pediatric parent cohort for a total of 522 participants ([Table 2](#)). In both cohorts, there were some patients who had at least one of the 18 survey questions missing an answer (142/197, 72.1% of adults and 104/325, 32% of pediatric parents). As such, data analyses are based on those who answered each question. In the adult cohort, the only significant difference in demographic characteristics between those who completed the entirety of the survey and those who did not was race distribution ($P=.004$), with 61% of noncompleters being African American compared to 46% of those who did complete it. In the pediatric cohort, the only statistically significant difference between survey completers and noncompleters was age, with noncompleters being significantly older ($P<.001$) than those who completed the survey.

The mean age was 58 (SD 17.3) years old for adult patients and 37 (SD 9.7) years old for pediatric parents. Overall, 65.6% (124/189) of adult patients and 85.8% (272/317) of pediatric parents were female, and 57.1% (104/182) of adult patients and 55.7% (176/316) of pediatric parents identified as African American. Less than half (72/181, 39.8%) of adult patients and a quarter (81/313, 25.9%) of pediatric parents reported educational attainment below a college degree, and 50.3% (91/181) of adult patients and 67.7% (212/313) of pediatric parents reported educational attainment at or above a bachelor's degree. The average duration of the patient-physician relationship was 4.3 years in the GIM sample and 3.3 years in the pediatric sample.

Table 2. Participant demographics.

| Participant demographics | Adult sample (n=197) | Pediatric parent sample (n=325) |
|---|----------------------|---------------------------------|
| Age (years), n (%) | | |
| 18-19 | 2 (1.0) | 5 (1.7) |
| 20-29 | 11 (5.8) | 55 (18.2) |
| 30-39 | 19 (10.0) | 138 (45.5) |
| 40-49 | 21 (11.1) | 69 (22.8) |
| 50-59 | 40 (21.1) | 29 (9.6) |
| 60 and older | 97 (51.1) | 7 (2.3) |
| Gender, n (%) | | |
| Female | 124 (65.6) | 272 (85.8) |
| Male | 65 (34.4) | 45 (14.2) |
| Race | | |
| White | 47 (25.8) | 76 (24.1) |
| African American | 104 (57.1) | 176 (55.7) |
| Asian | 17 (9.3) | 18 (5.7) |
| Hispanic or Latino | 8 (4.4) | 31 (9.8) |
| Mixed/Other | 6 (3.3) | 15 (4.7) |
| Educational attainment, n (%) | | |
| Less than high school graduate | 5 (2.8) | 3 (1.0) |
| High school graduate or GED ^a equivalent | 31 (17.1) | 20 (6.4) |
| Some college, no degree | 36 (19.9) | 58 (18.5) |
| Associate degree | 18 (9.9) | 20 (6.4) |
| Bachelor's degree | 31 (17.1) | 81 (25.9) |
| Graduate or professional degree | 60 (33.2) | 131 (41.9) |
| Length of relationship with physician (years), mean | 4.3 | 3.3 |

^aGED: General Educational Development.

Postvisit Survey Results

Impact of Comic on Patient Advocacy to Enhance Patient-Physician-EHR Interactions

Nearly three-quarters of adult patients (115/162, 71.0%) and pediatric parents (224/313, 71.6%) agreed the comic “encouraged them to be more involved in the EHR.” Almost half of all participants (76/161, 47.2% of adult patients; 137/311, 44.1% of pediatric parents) agreed that the comic made them “feel more empowered about getting involved with the computer.” As a result of the comic, approximately a third of all participants (60/162, 37.0% of adult patients; 81/310, 26.1% of pediatric parents) asked to see the screen and to be more involved with their physician’s computer use by asking “to review their chart in EHR” (61/162, 37.7% of adult patients; 92/308, 29.9% of pediatric parents). As well, as a result of the comic, over one-third of participants (74/161, 46.0% of adult patients; 118/309, 38.2% of pediatric parents) felt more comfortable “asking their doctor to pay full attention to them if a sensitive topic came up.” More than half of participants (93/161, 57.8% of adult patients; 169/310, 54.5% of pediatric

parents) felt that because of the comic, they were “more likely to get involved with their doctor’s computer use at future visits.” The remainder of the responses given on the entire survey are provided in [Multimedia Appendix 3](#).

Based on univariate analyses, African American and Hispanic participants were more likely than White participants to “ask to see the screen” and “be involved due to the comic” (median 4 vs 3 for both; adult $P=.01$, $P=.01$; pediatric parent $P=.02$, $P=.006$, respectively). In both groups, lower educational attainment level was associated with significantly higher rates of self-reported advocacy behaviors to promote patient EHR engagement. Specifically, in the adult patient population, this included increased rates of “calling for physician attention” ($\rho=-0.17$, $P=.04$); and in the pediatric cohort, these behaviors included “asking to see the screen” ($\rho=-0.18$, $P=.003$) and “asking to be involved with the EHR” ($\rho=-0.19$, $P<.001$) as a result of the comic. Additionally, adult female patients were more likely than male patients to ask to be involved with their physician’s computer use due to the comic (median 4 vs 3, $P=.003$); no gender differences were found in the pediatric parent population. Multivariate logistic regression analyses

(Table 3) confirmed independent associations with education, with race and ethnicity remained in the pediatric cohort. especially in the pediatric cohort. In addition, robust associations

Table 3. Association between demographic characteristics and patient perceptions of comic in multivariate analyses.^a

| Characteristic | Statement "Because of the comic..." | | | | | |
|---|-------------------------------------|---|--|---|--|--|
| | I asked to see the screen | I asked to be more involved with the computer | I felt more empowered about getting involved with the computer | I felt more comfortable asking for the physician's full attention | I am more likely to get involved with the computer in the future | I think it's a good way to encourage involvement with the computer |
| Adult cohort | | | | | | |
| Female gender (vs male), odds ratio (95% CI) | 1.01 (0.45-2.28) | 0.78 (0.35-1.72) | 1.49 (0.70-3.16) | 0.96 (0.45-2.05) | 1.55 (0.72-3.32) | 1.65 (0.74-3.67) |
| Education ^b , odds ratio (95% CI) | 0.70** (0.54-0.90) | 0.70** (0.54-0.90) | 0.82 (0.64-1.04) | 0.80 (0.63-1.01) | 0.81 (0.64-1.03) | 0.99 (0.77-1.28) |
| Race/ethnicity (vs white), odds ratio (95% CI) | | | | | | |
| African American | 2.00 (0.76-5.23) | 1.69 (0.66-4.31) | 1.05 (0.45-2.48) | 1.12 (0.47-2.64) | 1.49 (0.63-3.51) | 1.52 (0.61-3.76) |
| Asian | 2.21 (0.54-8.97) | 1.26 (0.30-5.27) | 1.08 (0.30-3.88) | 1.24 (0.34-4.46) | 2.72 (0.72-10.19) | 1.11 (0.30-4.11) |
| Hispanic | 3.49 (0.59-20.52) | 2.81 (0.49-16.22) | 1.50 (0.28-8.22) | 3.18 (0.52-19.53) | 2.90 (0.47-18.06) | 3.70 (0.39-35.42) |
| Other | N/A ^c | N/A | N/A | 0.50 (0.04-5.55) | 1.05 (0.13-8.70) | 1.37 (0.13-14.79) |
| Model chi-square (<i>df</i>) | 15.6 (5) | 14.2 (5) | 5.2 (5) | 7.2 (6) | 8.4 (6) | 3.8 (6) |
| <i>P</i> value | 0.008 | 0.01 | 0.39 | 0.31 | 0.21 | 0.71 |
| <i>n</i> | 135 | 135 | 135 | 138 | 138 | 140 |
| Pediatric cohort | | | | | | |
| Female gender (vs male), odds ratio (95% CI) | 0.86 (0.39-1.91) | 0.95 (0.43-2.10) | 1.13 (0.56-2.31) | 1.32 (0.64-2.75) | 0.64 (0.32-1.30) | 0.97 (0.46-2.06) |
| Education ^b , odds ratio (95% CI) | 0.75** (0.61-0.91) | 0.74** (0.61-0.90) | 0.76** (0.63-0.92) | 0.72*** (0.59-0.87) | 0.78* (0.65-0.95) | 0.84 (0.68-1.05) |
| Race/ethnicity (vs white), odds ratio (95% CI) | | | | | | |
| African American | 2.41 (0.99-5.87) | 3.68** (1.45-9.34) | 1.34 (0.71-2.54) | 0.93 (0.48-1.80) | 1.41 (0.76-2.61) | 1.41 (0.73-2.72) |
| Asian | 3.64 (0.97-13.59) | 5.75** (1.54-21.42) | 2.04 (0.68-6.12) | 2.81 (0.93-8.51) | 1.08 (0.37-3.17) | 0.72 (0.24-2.15) |
| Hispanic | 5.03** (1.66-15.20) | 6.17** (1.95-19.56) | 1.72 (0.68-4.35) | 1.25 (0.48-3.21) | 1.29 (0.51-3.27) | 0.87 (0.33-2.30) |
| Other | 4.54* (1.14-18.06) | 12.60*** (3.00-52.98) | 7.28** (1.82-29.11) | 2.67 (0.80-8.87) | 4.11* (1.04-16.32) | 2.75 (0.56-13.46) |
| Model chi-square (<i>df</i>) | 23.9 (6) | 34.3 (6) | 20.3 (6) | 18.6 (6) | 15.1 (6) | 8.2 (6) |
| <i>P</i> value | <.001 | <.001 | 0.003 | 0.005 | 0.02 | 0.22 |
| <i>n</i> | 290 | 287 | 290 | 288 | 288 | 291 |

^aNumbers in table are odds ratios (95% CI) from 6 separate multivariate logistic regression models for agreeing with given statement (agree or strongly agree vs not). * $P < .05$, ** $P < .01$, *** $P < .001$.

^bTreated as a continuous measure using integer scores for educational level (higher scores = more education).

^cNot applicable.

Satisfaction With Physician EHR Use

The large majority of adult patients (151/192, 78.6%) and pediatric parents (294/323, 91.0%) agreed that their physician “made sure they could see the screen” during the clinic visit and “made sure they could talk face to face even though they were using the computer” (180/194, 92.8% and 301/325, 92.6%, respectively). Most adult patients (128/189, 67.7%) and pediatric parents (260/325, 80%) agreed that their physician encouraged them to “interact with the computer” (eg, showing information in EHR, encouraging them to use the patient portal). Nearly three-quarters of adult patients (125/172, 72.7%) and pediatric parents (247/325, 76%) agreed their “physician valued the computer and was positive about the benefits.”

Perceptions of Physician Communication at Current Visit Compared to Prior Visits

When comparing the current visit with recollections of prior visits with the same physician, more than half of participants (109/163, 66.9% of adult patients; 186/325, 57.2% of pediatric parents) agreed that at the current visit, their physician “used the computer more effectively to communicate with them” and was “less distracted by the computer and more focused on them” (97/157, 61.8% of patients; 186/325, 57.2% of pediatric parents). Further, compared to prior visits, more than half of all participants (99/160, 61.9% of adult patients; 179/325, 55.1% of pediatric parents) agreed that they “understood more about their/their child’s health and plan,” and 56.2% (81/144) of adult patients and 46.6% (131/281) of pediatric parents were “more satisfied with their relationship with their/their child’s doctor because of how they used the computer with them.”

Follow-up Telephone Interview

A total of 148 adult patients (148/197, 75.1%) and 196 pediatric parents (196/325, 60.3%) were interested in participating in follow-up phone interviews. Patients were randomly selected from this group, and a total of 83 adult patients (83/148, 56.1%) and 60 pediatric parents (60/196, 30.6%) were called to reach 50 completed interviews for each cohort. Follow-up phone interviews were conducted on average 8 months (range 3-12

months) post visit. There were no significant differences in age, sex, race, educational attainment level, or length of physician relationship between those that completed phone interviews, those that were interested in taking part in phone interviews but did not (eg, they were unavailable or were not randomly selected to take part), and those that were only initially surveyed after their visit and were not interviewed by phone because they declined to take part.

All pediatric parents (50/50) and 90% (45/50) of adult patients remembered the comic, and almost half of adult patients (23/50, 46%) and pediatric parents (21/50, 42%) recalled at least one of the comic’s three ABC best-practice behaviors without prompting. When asked if they used the advocacy behaviors suggested in the comic at subsequent physician visits, adult patients reported that they were more likely to ask to see the screen ([Multimedia Appendix 2](#), question 3, median response 3 vs 4, $P=.006$), and pediatric parents reported increases in asking to see the screen ([Multimedia Appendix 2](#), question 3, median response 3 vs 4, $P<.001$) and calling for physician attention ([Multimedia Appendix 2](#), question 4, median response 3 vs 4, $P<.001$). Pediatric parents also felt that the comic had encouraged them to speak up and get more involved with physician computer use since the index visit ([Multimedia Appendix 2](#), question 2, median response 4 vs 4, $P=.02$) and that it made them feel more empowered to get involved with computer use at future visits ([Multimedia Appendix 2](#), question 5, median response 3 vs 4, $P<.001$). There were no significant differences in adults feeling more empowered to get involved at future visits ([Multimedia Appendix 2](#), question 5, median response 4 vs 4, $P=0.23$) or in either group thinking the comic was effective in encouraging continued involvement with the computer at physician visits ([Multimedia Appendix 2](#), question 6, median response 5 vs 4, $P=.26$ for adults; median response 4 vs 4, $P=.06$ for pediatrics).

Open-ended question responses were collectively pooled. Content analysis identified unique themes, subthemes, and representative quotations in order to build a picture of the respondents’ collective experiences ([Table 4](#)) [55].

Table 4. Themes and subthemes relevant to the educational comic and EHR use.

| Themes and subthemes | Representative quotes |
|---|--|
| Patient perceptions | |
| EHR ^a awareness | “The effort as a whole did make me more aware of the computer and I feel like, oh, I notice the screen and the doctor’s use” |
| Screen viewing | “The comic was great because I didn’t know it was my right to look at the computer” |
| Asking questions | “The comic was really good; I wasn’t sure if you could ask questions” |
| Time for EHR involvement | “Patients often feel like they are rushed, the comic gives assurance that its okay to ask questions” |
| Encouraging engagement | “I already do the ABCs; for someone who is more bashful or reserved, the comic may be more helpful.” |
| Patient behaviors | |
| EHR engagement | “I’ve had several appointments since the appointment and it’s been much better, I was very involved, one physician did on a laptop which was cool so I could see.” |
| Asked to see screen | “Comic was first time to see the screen. Comic helped me ask, prior to the visit I had never asked to see the screen” |
| Asked for clarification | “I ask can I see the screen, talk to me about what you see” |
| Asked about clinician behaviors | “Asked him to further explain to me what he was doing and inputting on the computer” |
| Corrected errors | “Asked to see my record and make corrections” |
| Watched what clinician was typing | “I liked to see what she is typing. Also it helps me understand what is happening during our visit. Great idea.” |
| Asked to see things in the EHR | “When showing child growth, I asked to see the graph” |
| Physician behaviors | |
| EHR use in visit | “My doctor is awesome, when she’s pulling up my history and my labs she pulls up the screen so I can see it and she looks at my medications and she asks me are you taking this, are you still taking them twice a day” |
| Patient portal use | “My doctor involved me by encouraging me to go online and look at the chart” |
| Suggestions for comic modification | |
| Improved readability | “Bigger font in speech bubbles, more lay language” |
| Translation | “Have it in other languages such as Spanish” |
| Increased visibility | “Place cartoon in rooms, on the wall” |
| Provide script examples | “Like using key phrases / trigger points, give phrases that patients can use” |
| Orientation to EHR content | “Give more examples of what one may find on computer screen that he/she may wish to see” |
| Highlight benefits of involvement | “Give more detailed examples of the benefits of getting involved” |
| Highlight drawbacks of uninvolvement | “I would add an example that would scare them to get involved” |
| Suggestions for EHR engagement | |
| Patient-facing portions of EHR | “Have a portion of the EHR where pts can interact w/computer themselves” |
| Mobile technology | “A tablet to follow along with the chart as doc is on computer” |
| Patient portal training | “If someone showed me how to use MyChart” |
| General technology training | “Teaching us how to use a computer and how to learn” |
| Room ergonomics | “Screen where patient and doc can see without doc’s back to patient” |
| Nursing involvement | “Nurses can tell patients/parents to ask dr to share computer screen” |
| Highlight importance of patient involvement | “Maybe take a moment at the beginning to reiterate what they’re doing every step of the way on the computer and let patients know that they have the right to see the screen - gives partnership in their own personal care” |
| Physician training | “Train the doctor to be move involved” |
| Reset physician EHR expectations | “Wish drs had to always show info unless confidential info is on screen” |

^aEHR: electronic health record.

Discussion

To our knowledge, this is the first study evaluating the impact of an educational comic on patient advocacy for enhanced patient-physician-EHR interactions. This easily replicable intervention may help improve patient self-advocacy for patient-centered engagement with the EHR in pediatric and adult primary care settings, which can promote both patient education and satisfaction with physician EHR use. Importantly, the effect was more pronounced in African American and Hispanic patients and patients with lower levels of educational attainment.

Prior studies have found that non-White patients, those with lower educational attainment, and non-English-speaking patients experience health care disparities which may result in poor health outcomes [35-47]. These patients may also come to visits with lower levels of health literacy and agency, which can be associated with difficulty understanding their diagnoses and treatment plans [35-47]. The open-ended comments in our study (Table 4) highlighted that some patients do not feel empowered to ask questions during their visits, and handing out the educational comic may serve as a simple but powerful invitation to speak up and ask questions of their physicians.

Additionally, patients from disadvantaged backgrounds are more likely to report distrust of their health care team when compared to patients from nondisadvantaged social and educational backgrounds [44,45,47,56]. Sharing the EHR screen and enhancing transparency and engagement with the EHR may increase a patient's sense of partnership and trust with their physician, which may help promote increased trust of the medical system [26,44-47]. Moreover, patients from disadvantaged groups may need more formal encouragement to engage with their physicians and the EHR, which is important because enhanced engagement with providers and health care technology can help increase patient understanding of care plans and improve preparation for future visits [6,12,44-47,57]. Our educational comic may be used as a tool to empower vulnerable patients to be more engaged in their care and promote agency. In addition, patients with limited health literacy may rely on health information from social media and blogs, which can contain lower quality health information [47]. Encouraging patients to ask their physicians questions may help dispel health myths, promote health literacy, and help reduce health disparities [44-47].

With regard to patient satisfaction with physician EHR use, patients reported that their physicians demonstrated more patient-centered behaviors when using the EHR at the index visit as compared to prior visits. This may be due to the patient's increased EHR engagement during the visit, which could have prompted physicians to engage in more patient-centered EHR behaviors. Future research is needed to better understand how enhanced patient EHR engagement is perceived by physicians and the impact on physicians' EHR-related behavior.

Lastly, there were no significant differences in either adult or pediatric respondents thinking the comic was effective at encouraging continued involvement with the computer on phone follow-up. However, what is perhaps more important is that

when describing the comic's impacts on specific behaviors at subsequent physician visits, both adult and pediatric patients reported increased use of the self-advocacy behaviors in the comic since their initial visit, particularly in the pediatric cohort; this perhaps suggests that it may have been effective in contributing to lasting impacts on their subsequent EHR interactions, especially when advocating on behalf of someone else (ie, their child).

Our study has several limitations. First, it was a single-institution study, and we had an overrepresentation of women and advanced degree holders in our sample, both of which may limit generalizability. In addition, while it may be difficult to directly compare pediatric parent to adult patient responses, findings from pediatric parents may be generalizable to family members who accompany adult patients to visits or serve as proxies for those who cannot speak or advocate for themselves. Our study did not include a control group, and we did not conduct a preintervention survey due to resource constraints. To adjust for this, the postvisit survey asked participants to rate their perceptions, advocacy behaviors, and satisfaction with their physician's EHR use at the current visit as compared to their recollection of these measures from prior visits with the same providers. These responses may have been subject to recall and response bias, and phone interviews may have been affected by the variable follow-up period. Our findings were dependent on reports from adult patients and pediatric parent participants without direct observation of physician or patient behavior. Further, we did not include a control group with a text-only nongraphic version of the comic, so it is not possible to say if a nongraphic intervention would have had the same impacts. Lastly, physicians were generally deemed by their patients to be adept at engaging them with the EHR, perhaps because they were biased to providing positive responses, and physicians were aware that the study was occurring, which may have influenced their EHR behaviors. In order to help minimize this impact, physicians were not shown the patient comic or the survey.

Further work is needed to understand how to tailor educational comics to different patient populations and clinical settings, such as the inpatient hospital environment, to effectively engage patients and physicians with the EHR. While this educational intervention targeted patients, it is also important to teach patient-centered EHR behaviors to physicians to promote patient-physician-EHR engagement [20-26,58,59], and these efforts should be pursued in tandem. Additionally, EHRs should evolve to account for user experience, patient health literacy levels, and language needs to help reduce the digital divide and health disparities [19,60-68].

In conclusion, to our knowledge, this is the first study evaluating the impact of an educational comic intervention on patient-centered EHR use and patient self-advocacy for EHR engagement. We found that our educational comic was well received, participant ratings showed benefits in the outcomes measured, and there was no harm to participants as a result of their participation. Our comic may be effective in promoting patient-driven initiatives to enrich patient-physician-EHR interactions and may be most impactful in engaging African American patients, Hispanic patients, and patients with lower

educational attainment. This simple intervention can be easily replicated, and future work should focus on studying the impact of the educational comic in other clinical settings and objectively measuring behaviors related to the patient-physician-EHR

interaction. Educational comics should be considered in future initiatives to promote patient education and humanistic patient-centered EHR use.

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Adult patient comic initial survey.

[\[DOCX File, 21 KB - humanfactors_v8i2e25054_app1.docx\]](#)

Multimedia Appendix 2

Adult patient phone interview script.

[\[DOCX File, 17 KB - humanfactors_v8i2e25054_app2.docx\]](#)

Multimedia Appendix 3

Patient perceptions of comic intervention: postvisit survey results.

[\[DOCX File, 18 KB - humanfactors_v8i2e25054_app3.docx\]](#)

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Abbreviations

EHR: electronic health record

GIM: general internal medicine

PPC: pediatric primary care

SQUIRE: Standards for Quality Improvement Reporting Excellence

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Original Paper

Developing a Decision Aid to Facilitate Informed Decision Making About Invasive Mechanical Ventilation and Lung Transplantation Among Adults With Cystic Fibrosis: Usability Testing

Katherine L Dauber-Decker¹, PhD; Melissa Basile¹, PhD; D'Arcy King¹, PhD; Jennifer Polo¹, BA; Karina Calise², BSc; Sundas Khan¹, MD; Jeffrey Solomon¹, BFA; Daniel Dunne³, MA; Negin Hajizadeh¹, MD, MPH

¹Donald and Barbara Zucker School of Medicine at Hofstra/Northwell, Feinstein Institutes for Medical Research, Center for Health Innovations and Outcomes Research, Manhasset, NY, United States

²School of Health Professions and Human Services, Hofstra University, Hempstead, NY, United States

³iDEAL Institute, Loyola Marymount University, Los Angeles, CA, United States

Corresponding Author:

Jennifer Polo, BA

Donald and Barbara Zucker School of Medicine at Hofstra/Northwell

Feinstein Institutes for Medical Research

Center for Health Innovations and Outcomes Research

600 Community Drive

Manhasset, NY, 11030

United States

Phone: 1 3474004684

Email: jpolo1@northwell.edu

Abstract

Background: Cystic fibrosis (CF) is a life-limiting genetic disease that causes chronic lung infections. We developed an internet-based decision aid (DA) to help patients with CF make better informed decisions regarding treatments and advance care planning. We built the DA around two major treatment decisions: whether to have a lung transplant and whether to agree to invasive mechanical ventilation (intubation).

Objective: This study aims to conduct usability testing of the InformedChoices CF DA among key stakeholder groups.

Methods: We performed a patient needs assessment using *think-aloud* usability testing with patients with CF, their surrogates, and CF clinicians. *Think-aloud* participants provided feedback while navigating the DA, and after viewing, they answered surveys. Transcripts from the *think-aloud* sessions and survey results were categorized into common, generalizable themes and optimizations for improving content, comprehension, and navigation. We assessed the ease of use of the DA (System Usability Scale) and also assessed the participants' perceptions regarding the overall tone, with an emphasis on emotional reactions to the DA content, level of detail, and usefulness of the information for making decisions about either intubation or lung transplantation, including how well they understood the information and were able to apply it to their own decision-making process. We also assessed the DA's ease of navigation, esthetics, and whether participants were able to complete a series of usability tasks (eg, locating specific information in the DA or using the interactive survival estimates calculator) to ensure that the website was easy to navigate during the clinic-based advance care planning discussions.

Results: A total of 12 participants from 3 sites were enrolled from March 9 to August 30, 2018, for the usability testing: 5 CF clinicians (mean age 48.2, SD 12.0 years), 5 adults with CF, and 2 family and surrogate caregivers of people with CF (mean age of CF adults and family and surrogate caregivers 38.8, SD 10.8 years). Among the 12 participants, the average System Usability Scale score for the DA was 88.33 (*excellent*). *Think-aloud* analysis identified 3 themes: functionality, visibility and navigation, and content and usefulness. Areas for improvement included reducing repetition, enhancing comprehension, and changing the flow. Several changes to improve the content and usefulness of the DA were recommended, including adding information about alternatives to childbearing, such as adoption and surrogacy. On the basis of survey responses, we found that the navigation of the site was easy for clinicians, patients, and surrogates who participated in usability testing.

Conclusions: Usability testing revealed areas of potential improvement. Testing also yielded positive feedback, suggesting the DA's future success. Integrating changes before implementation should improve the DA's comprehension, navigation, and usefulness and lead to greater adoption.

KEYWORDS

usability; medical informatics; clinical decision support; cystic fibrosis; advance care planning

Introduction

Background

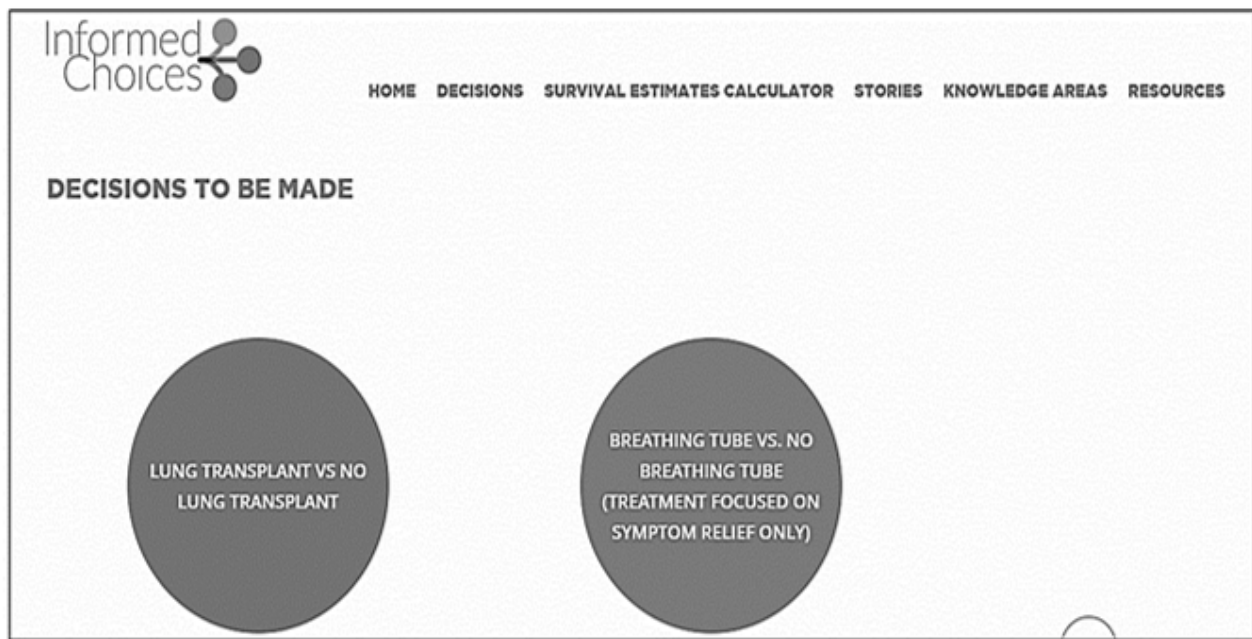
Cystic fibrosis (CF) is a life-limiting, progressive genetic disease that causes chronic lung infections [1,2] and persistent symptoms, including coughing, pneumonia, bronchitis, wheezing, difficulty breathing, and lack of weight gain and growth [3]. The average life expectancy for a person with CF is currently estimated at approximately 37 years [4]. However, because of variability among patients related to the natural course of pulmonary decline, it is difficult to estimate prognoses [5-10]. Therefore, it is often unclear when clinicians should initiate advance care planning (ACP) discussions with patients with CF. ACP allows patients' early consideration of the kind of end-of-life care they may want while they are able to fully understand the implications of different treatment options. ACP is recommended by the American College of Chest Physicians [11]; however, it is not widely practiced in patients with CF [12]. Encouraging patients to plan their care is important so that their end-of-life desires and needs are fully acknowledged and protected.

As part of the Cystic Fibrosis Foundation initiative to foster innovative approaches in CF-specific palliative care, our team at the Center for Health Innovations and Outcomes Research at Northwell Health undertook a multiphased study to develop an internet-based patient decision aid (DA) called InformedChoices [13]. We developed DA content around 2 crucial decisions that advanced patients with CF commonly face as their condition progresses: whether to have a lung transplant and whether to agree to intubation (invasive mechanical ventilation [IMV]) in the event of acute respiratory failure (Figure 1). The goal of the DA is to increase preference-congruent care at the end of life for patients with advanced stage CF by fostering shared decision-making conversations among adults with CF, their clinicians, and family caregivers. Therefore, the purpose of the DA is to be used by the CF clinician with their patients with CF and family members during outpatient clinic visits. The development of our DA content was guided by several key bodies of literature—DA design—specifically the International Patient Decision Aid Standards (IPDAS) Collaboration criteria for DA design, which presents a checklist of quality standards for the development of

DA content [14]. For example, the IPDAS criteria provides patients a range of visual options for viewing prognostic survival estimates. Therefore, we included icon arrays, percentages, and graphs to convey information on the prognostic outcomes [15]. IPDAS also encourages the inclusion of methods to clarify patients' values and goals of care. This is known as *preference elicitation*. Previous work encourages interactive and hierarchical approaches to eliciting preferences [16-18]. Therefore, we chose an interactive exercise offering patients a range of possible outcomes related to both lung transplantation and IMV. For each risk and benefit offered, users are able to slide a tab along a continuum from not important to very important. Finally, patients could view their results with the risks and benefits placed in hierarchical order from most important to least important. Additional criteria that we considered when designing the DA and on which we focused our usability testing included the use of plain language that could be understood by end users of various educational backgrounds, using stories or narratives that represent a range of outcomes, and presenting information in a balanced manner. Regarding the last point, when offering the risks and benefits of the various treatment options, we presented this information in side-by-side columns to allow clear visual representation of the risks and benefits.

We also explored the literature on both current DA development specific to ACP decision making [19-21] and literature on specific ACP and palliative care concerns faced by people with CF [22,23]. From this literature, we learned that individuals incorporate various types of knowledge into their decision making and often draw on previous lived experiences, which may *compete* with the biomedical information being conveyed. This influenced the study design of our usability testing, that is, the extent to which competing knowledge frameworks may actually impact users' ability to understand the biomedical information being conveyed. This is reflected in our usability testing questions, which seek to determine the extent to which users not only *understood* the information but were then able to apply it to their own medical condition. Finally, there is a more recent body of literature on developing models of primary palliative care for CF. The focus is on allowing CF care teams to offer basic palliative care services, including ACP and goals of care discussions to people with CF on an ongoing basis, throughout the life course [22,23].

Figure 1. Cystic fibrosis internet-based decision aid—decisions page.



Objectives

Our DA is meant to be used in such contexts, that is, shared decision making among patients with CF, CF providers, and family and surrogate caregivers. Therefore, one of our usability testing goals was to ensure that CF clinicians were comfortable conveying the information contained in the DA about advanced CF treatments and that patients and caregivers could understand the information. We also sought to assess the possible emotional reactions to the information among patients and their caregivers. Usability testing allowed us to assess these factors with our target end users before rollout of a larger scale feasibility and acceptability study undertaken in outpatient clinic settings.

Finally, the design of the DA was further informed by a qualitative needs assessment where we interviewed adult patients with CF and family caregivers about their information needs as they pertained to ACP and CF treatment decisions and any previous discussions with their clinicians about both intubation and lung transplantation [13]. We also informally surveyed CF clinicians, asking them to tell us what information they felt their patients needed to know to make an informed decision about both intubation and transplant and to provide us with relevant peer-reviewed articles on which to base DA content. Guided by the abovementioned IPDAS criteria, review of literature, and direct stakeholder engagement, the DA's website content includes descriptions of both intubation or IMV and lung transplantation, including the risks and benefits of each procedure. We also provided tailored prognostic estimates using multiple displays of data to accommodate different levels of health numeracy and preferences for information styles [24]. The needs assessment revealed that several participants preferred to learn about IMV and lung transplantation by hearing directly from patients with CF who had experienced intubation or lung transplantation. They expressed a desire for a more personal connection, that is, to know *what it felt like* to go through lung transplant or IMV, as opposed to the more clinical descriptions

of the procedures that they were often given by their providers. This type of information allowed for greater emotional engagement with the DA content, which we believe may appeal to certain individuals' learning styles and preferences for information. Therefore, we conducted interviews with patients with CF or family members about these treatments and edited them for inclusion in the DA. We also included additional content areas covering CF-specific mental health care, palliative care, and ACP based on what CF clinicians believed to be important for informed decision making related to CF ACP. Furthermore, from the needs assessment, we discovered that people's desire for information varied, with some people wanting to know very detailed information about their treatment options and others preferring to know less. On the basis of this, our DA design allowed for basic as well as detailed information, as we allow individuals to navigate to a resources page that contains all of the references we used to write DA content (to accommodate those with high information-seeking preferences) and preference elicitation exercises for both IMV and lung transplantation, per IPDAS guidelines. Our overall goal was to ensure that our DA could accommodate a wide array of learning styles and information preferences to ensure the uptake of the information presented.

Following the initial design of the DA, we performed usability testing to maximize adoption, comprehension, and end user benefit before the final phase of the study—feasibility and acceptability testing of the DA among adults with CF, providers, and family members in ACP shared decision-making conversations in outpatient clinic settings. Although the DA is intended for shared decision-making conversations, our focus in undertaking a usability testing phase was to assess, among the 3 key stakeholder groups (patients, clinicians, and family surrogate caregivers), individual-level comprehension of the written content; perceptions of the usefulness for communicating about the risks and benefits of both pursuing or not pursuing lung transplant; and accepting or refusing intubation, visibility,

and ease of navigating the website. Our intention was to ensure that we had addressed any potential design problems and that content was understandable before the rollout of a larger scale feasibility and acceptability study. Herein, we present the results of the testing conducted among key CF stakeholders.

Methods

Study Design and Data Collection

Eligible participants were clinicians, patients, and surrogate caregivers who met the criteria described in the *Eligibility* section. On enrollment, each participant completed a basic demographic and health survey. Participants were then shown the DA either in person or remotely via Webex, a Health Insurance Portability and Accountability Act–compliant web-based conferencing platform. In both scenarios, a member of the research team observed the process and took detailed notes. Participants were asked to navigate through the DA at their own pace and click on the pages in any order they wished. Participants were encouraged and reminded throughout the testing session to *think aloud* as they progressed through the content and to voice their comments and reactions to the information and images in real time. This process was captured using Hypercam (Microsoft), a screen capture and audio recording software. Once participants viewed the DA, they were asked to complete 3 questionnaires to elicit their postexperience feedback. First, the validated System Usability Scale (SUS) [25] was used to measure the ease of use of the DA. The next 2 questionnaires were developed specifically to assess this specific CF DA. One questionnaire asked open- and closed-ended questions designed to measure the participants' perceptions of the overall tone, with an emphasis on emotional reactions to DA content (eg, personalized prognostic estimates indicating survival over a 3-year period and reactions to images of an intubated patient), level of detail, and usefulness of the information for making decisions about either intubation or lung transplantation, including how well people understood the information and were able to apply it to their own decision-making process. This questionnaire also addressed the ease of navigation and esthetics of the DA. The other questionnaire focused on having participants complete a series of usability tasks (eg, locating specific information in the DA or using the interactive survival estimates calculator) to ensure that the website was easy to navigate during the clinic-based ACP discussions (Multimedia Appendices 1–4). We also administered participant demographics surveys (Multimedia Appendix 5 and Multimedia Appendix 6). All questionnaires were administered directly via REDCap, where the responses were stored, anonymized, and exported to Excel for analysis. All Hypercam recordings were transcribed for qualitative analysis. Feedback from the surveys and recordings were coded into usability themes, as described in *Data Analysis* section.

Eligibility

Clinician Participants

Doctors, other advanced practice providers (nurses, nurse practitioners, and respiratory therapists), or social workers who treat patients with CF aged >18 years were eligible for the study.

Patients

Patients with lung function score of forced expiratory volume in the first second <55% and/or clinician's assessment of moderate to advanced stage CF, who had already undergone lung transplant, who were aged >18 years, and who speak English were eligible.

Surrogate Caregiver Participants

English-speaking individuals aged >18 years and currently caring for patients who meet the inclusion criteria mentioned earlier and caregivers of patients who died within the year before enrollment were eligible. Caregivers were primary caregivers and decision makers for people with CF and either parents or significant others of adults with CF; however, they did not need to be related to the patients who were enrolled in the study (ie, we did not enroll patients and caregivers as dyads).

In addition, all those participating remotely were required to have access to a computer with internet capability and a web camera installed or attached to their computer.

Recruitment and Consent

All participants were recruited from the Northwell Health CF Care Center, the University of Pennsylvania Perelman Center for Advanced Medicine, or the University of California San Diego Health Adult Cystic Fibrosis Program. Clinicians were recruited by the nonclinician members of the research team (ie, research coordinators) to avoid potential pressure to participate from their clinician peers who were members of the research team. Clinician-specific informed consent forms specifically stated that participation was voluntary and that decisions to not enroll in the study would not impact their employment. After being approached by a member of the research team at their respective sites, interested patients, surrogate caregivers, or clinicians were then referred to the research team at Northwell Health, the lead study site, where an investigator reviewed the main points of the study, answered any additional questions, and scheduled a time for the testing session. For in-person testing, written informed consent was obtained on site before initiating the testing session. For remote consent, the Northwell Health institutional review board–approved methods for remote consent were used. This involved using a phone script and sending consent forms via email before the scheduled testing day.

All participants received US \$100 compensation for their time, regardless of their stakeholder groups. Before the initiation of our study, we obtained approval from the Northwell Health institutional review board. The funding agency had no role in the design of the study.

Data Analysis

Audios from the Hypercam recordings were transcribed and analyzed qualitatively by the Northwell Health Usability Lab to identify usability issues, including whether users were able to complete assigned tasks, and to identify any barriers encountered (eg, whether content was understood and whether users were able to navigate efficiently through the DA). Usability Lab members performed a thematic analysis of the transcripts from the Hypercam recordings. This involved coding

the transcripts into the following themes: functionality, visibility and navigation, and content and usefulness. Members of the Usability Lab first met to ensure that all readers were coding in a similar fashion and establish interrater reliability. This was established through discussion following the individual coding of a subset of transcripts. Each transcript was then coded and analyzed by a member of the Usability Lab, and a summary of common suggestions for each theme was generated. Usability Lab members brainstormed and discussed changes that could be made to the website to address common issues and suggestions, which were then incorporated into a subsequent round of DA revisions.

Data from closed-ended questions administered during testing were summarized descriptively. Our sample size was limited to 12 participants; therefore, we were unable to perform rigorous

statistical analyses. As the established rule of usability testing states that 5 participants are sufficient to detect 80% of a product's usability issues [26], we chose a total sample of 12 participants, including 5 patients with CF, 5 clinicians, and 2 surrogate caregivers.

Results

Participant Characteristics

A total of 12 participants from 3 sites were enrolled from March 9 to August 30, 2018. Our sample included 5 CF clinicians (physicians, social workers, and nurse practitioners), 5 adults with CF (2 of whom had already undergone a lung transplant), and 2 family and surrogate caregivers of people with CF. A summary of the participants' demographic characteristics is available in [Table 1](#).

Table 1. Participants' demographic characteristics.

| Participant | Value |
|--|-------------|
| Clinicians (n=5) | |
| Age (years), mean (SD) | 48.2 (12.0) |
| Gender (female), n (%) | 5 (100) |
| Years of experience with patients with cystic fibrosis, mean (range) | 17.6 (9-29) |
| Profession, n (%) | |
| Physician | 2 (40) |
| Nurse practitioner | 1 (20) |
| Social worker | 2 (40) |
| Patients and surrogates^a (n=7) | |
| Age (years), mean (SD) | 38.8 (10.8) |
| Gender (female), n (%) | 3 (40) |
| Role, n (%) | |
| Patient | 5 (70) |
| Surrogate | 2 (30) |

^aFor the patients and surrogates group, 5 of the 7 participants provided age and gender information.

Quantitative Analysis of Questionnaire Responses

Our quantitative analysis was performed using the SUS [25] to assess the usability of the DA. Among the 12 participants, there was an average SUS score of 88.33, which indicates an *excellent*

score of *B* on the scale. The 5 clinicians gave the tool an average SUS score of 89.5; the 7 patients and surrogates gave an average score of 87.5. A summary of each participant's SUS scores is presented in [Table 2](#).

Table 2. System Usability Scale scores.

| Participant number | Participant category | System Usability Scale |
|--------------------|----------------------|------------------------|
| 1 | Clinician | 82.5 |
| 2 | Clinician | 90 |
| 3 | Clinician | 100 |
| 4 | Clinician | 92.5 |
| 5 | Clinician | 82.5 |
| 6 | Surrogate | 90 |
| 7 | Patient | 100 |
| 8 | Patient | 100 |
| 9 | Patient | 92.5 |
| 10 | Surrogate | 90 |
| 11 | Patient | 47.5 |
| 12 | Patient | 92.5 |
| — ^a | — | 88.33 |

^aThe average System Usability Scale score for all participants is presented in the last row. This does not imply missing data.

Thematic Analysis of Questionnaires and Think-Aloud Hypercam Recording Responses

Participants' comments from all *think-aloud* testing sessions and surveys were grouped into 3 overarching themes:

functionality, visibility and navigation, and content and usefulness. Major suggestions from these themes and accompanying participant quotes from the surveys and session transcripts are summarized in [Table 3](#) and in the following sections.

Table 3. Summary of participants' observations and comments and solutions to be implemented, grouped by usability theme.

| Usability theme and participants' observations and comments ^a | Solutions implemented |
|---|---|
| Functionality | |
| <p>The Breathing Tube and Lung Transplant page drawers do not flow logically:</p> <ul style="list-style-type: none"> “Situations in which a CFb patient... may need to decide about a breathing tube for procedures...this might go first...before we even look at the risks and benefits.” (Patient) | <p>Rearrange drawers (Figure 2):</p> <ul style="list-style-type: none"> Describe why it is important to think about getting a breathing tube or lung transplant Discuss factors associated with good and poor prognoses Provide more information about the treatment option and situations in which a patient may need to decide about the treatment List risks and benefits associated with the treatment option |
| Visibility and navigation | |
| <p>The details in the pictures showing intubation and tracheostomy are difficult to see:</p> <ul style="list-style-type: none"> “I wish I could see a bit more detail.” (Patient) “Add [an] enlarge feature to read the small labels.” (Patient) | <p>Add an enlarge feature to the images</p> |
| <p>The risks and benefits sections of the Breathing Tube and Lung Transplant pages are repetitive:</p> <ul style="list-style-type: none"> “I would take away the repetitive risks vs benefits tables for each procedure.” (Clinician) “...possibly revamping the pro and con section so that it doesn't have so much repeating info throughout.” (Patient) | <p>Condense the risks and benefits sections of these pages and eliminate the repetition</p> |
| <p>Participants were unclear on whether the survival estimates calculator provides estimates for before or after lung transplant or intubation:</p> <ul style="list-style-type: none"> “I actually took the estimates to mean posttransplant, so I feel like I would need to carefully clarify with the patients.” (Clinician) | <p>Visually emphasize the statement at the top of the page telling users that estimates are for before treatment by bolding the text and enlarging the font size (Figure 3)</p> |
| <p>Participants were concerned that some patients might take prognosis estimate percentages too literally:</p> <ul style="list-style-type: none"> “I just think that the concrete thinkers...could have a difficult time with that information even though you explained that they're estimates and how you got the estimates...that it's not written in stone. I think those concrete thinkers you know would...possibly have a little difficulty with that.” (Clinician) | <p>Emphasize the following statement by bolding the text: “Remember these are only estimates and the numbers may not apply specifically to you” (Figure 4)</p> |
| <p>Users need to scroll all the way back to the top of the Stories page to exit a story:</p> <ul style="list-style-type: none"> “I chose to read the transcripts and when I got to the end of the lengthy transcript I had to scroll all the way to the top to X out of the story.” (Clinician) | <p>Add a cancel button and close window option to the bottom of each story</p> |
| Content and usefulness | |
| <p>Patients with CF are motivated by their desire to survive for their children:</p> <ul style="list-style-type: none"> “Another thing that could be a question to ask in this area and it isn't pertinent to everybody but it sure has been pertinent to a lot of our patients who are considering transplant...they want to be around as long as they can be for their children.” (Clinician) | <p>Add the following phrase to the What's Important to Me slider: “Seeing my children grow up is important to me” (Figure 5)</p> |
| <p>Posttransplant pregnancy can pose challenges to both a mother with CF and their fetus:</p> <ul style="list-style-type: none"> Clinicians are trying to improve the process of explaining to patients that they “...can't physically carry [children themselves] but we can have [them] meet with an OBGYN or fertility providers before transplant to give [them] the best possible outcomes of having children in some other way or even...counseling about adoption..., surrogacy, different things like that.” (Clinician) | <p>Add descriptions of alternative options for becoming a parent, including adoption and surrogacy, to the decision aid (Figure 6)</p> |

^aThe quotations in this table were obtained from participant surveys and *think-aloud* transcripts. Participant categories are indicated in parenthesis following each quotation (ie, clinician, patient, or surrogate).

^bCF: cystic fibrosis.

Figure 2. Areas recommended for improvement on the cystic fibrosis decision aid. Drawer design as seen by study participants. Drawers on the Breathing Tube/Intubation (shown) and Lung Transplant (not shown) pages have now been reordered as follows: (1) why it is important to think about getting a breathing tube or lung transplant, (2) factors associated with good and poor prognoses, (3) more information about the treatment option, (4) situations in which a patient may need to decide about the treatment, and (5) risks and benefits associated with each treatment option. CF: cystic fibrosis; ICU: intensive care unit.

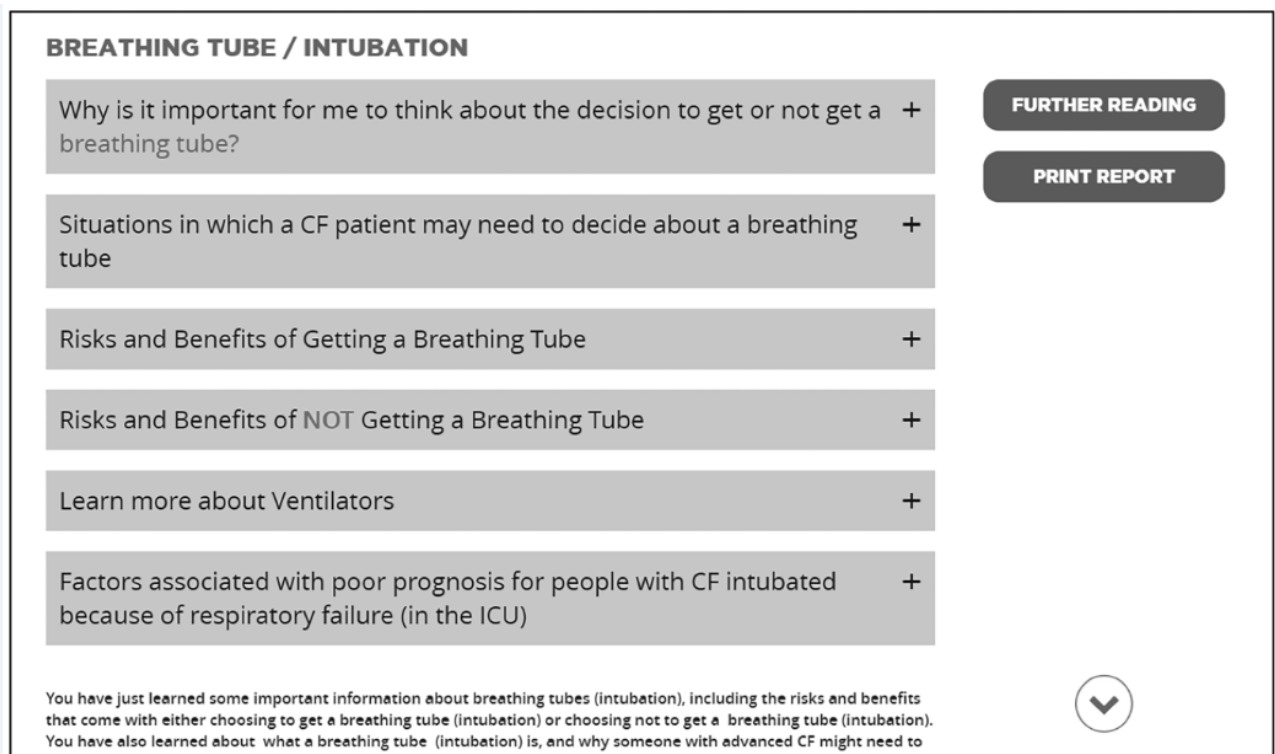


Figure 3. Survival estimates calculator. The initial phrase explaining the survival estimates calculator has been visually emphasized by bolding and enlarging the font. CF: cystic fibrosis.

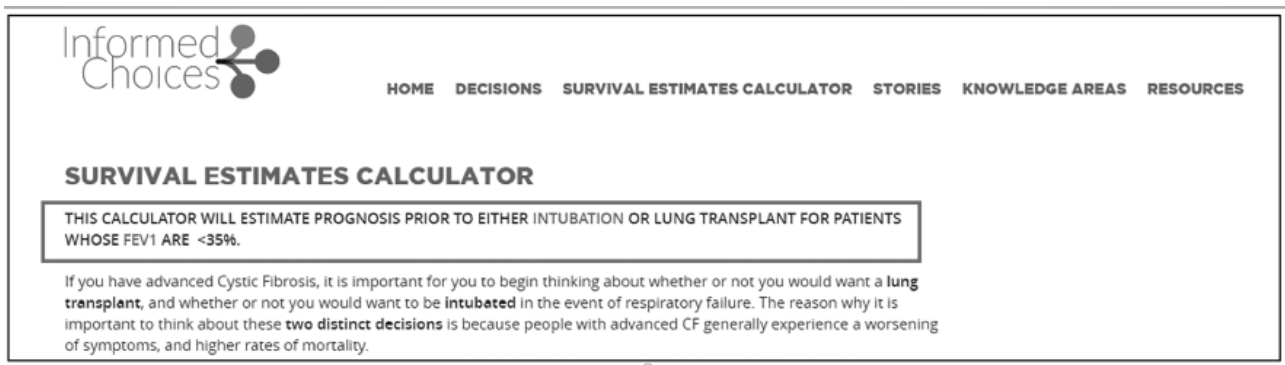


Figure 4. Survival estimates calculator page as seen by study participants. The statement that the percentages generated by the survival estimates calculator are only estimates and do not necessarily apply to individual patients has now been bolded for emphasis. CF: cystic fibrosis.

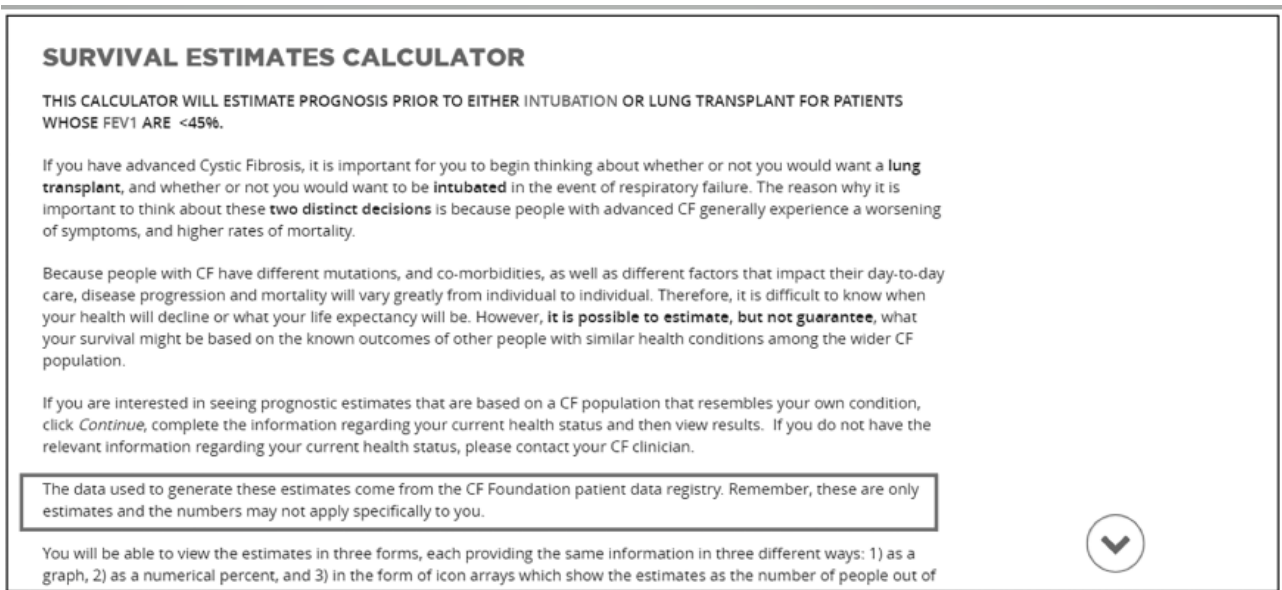


Figure 5. The addition of the phrase “Seeing my children grow up is important to me” to the What’s Important to Me slider will increase the usefulness of the slider for those who want to survive for their children.

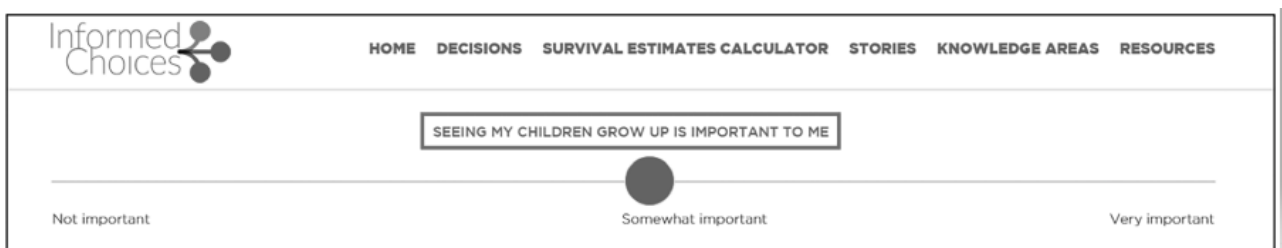
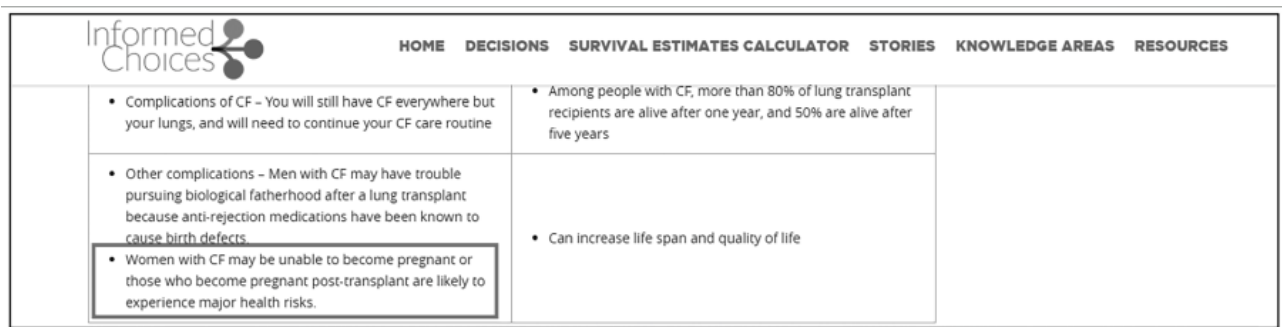


Figure 6. Pregnancy information as seen by study participants. Information about adoption and surrogacy has now been added to explain alternatives to pregnancy. The boxes indicate areas where text is being changed or emphasized to address user feedback. CF: cystic fibrosis.



Functionality

First, the changes in functionality were identified. For example, one suggestion involved the drawer design of the Breathing Tube and Lung Transplant pages. A drawer design helps to minimize the content to prevent the user from seeing too much text at one time and becoming overwhelmed. By expanding each *drawer* category, the user has the ability to view additional content of interest. One suggested optimization was that the drawers on the Breathing Tube and Lung Transplant pages should be reordered to improve the logic of the DA’s flow. We have reordered the drawers, accordingly, as shown in Table 3 (Figure 2). Reordering the topics to make the flow of

information more logical should make content more accessible and improve individual-level comprehension.

Visibility and Navigation

We also identified areas for improvement in the visibility of CF DA. For example, participants suggested that we enlarge the pictures displaying intubation and tracheostomy to increase the visibility of the smaller details of the images. One participant suggested that we:

add [an] enlarge feature to read the small labels.

With this change, users’ ability to engage with this content should improve.

In addition, several participants pointed out the repetition in the risks and benefits sections of the Breathing Tube and Lung Transplant pages. One participant from the patient and surrogate group suggested:

...possibly re-vamping the pro and con section so that it doesn't have so much repeating info throughout.

Condensing this section should eliminate repetition.

Next, several users were unclear on whether the survival estimates calculator provided patients with estimates before or after lung transplantation or intubation. In a survey response, one clinician said:

I actually took the estimates to mean post-transplant...

Accordingly, we have bolded the text and enlarged the font size of the statement at the top of the page, telling users that these are pretreatment estimates (Figure 3). In addition, there was concern among clinicians that some patients might take these percentages too literally. One of our clinician participants said:

I just think that the concrete thinkers...could have a difficult time with that information even though you explained that they're estimates and how you got the estimates...that it's not written in stone.

On the basis of this feedback, we have emphasized the following statement by bolding the text: "Remember these are only estimates and the numbers may not apply specifically to you" (Figure 4). These changes should help with users' emotional responses to and individual-level understanding of the prognostic estimates so that they can better understand and use this information.

Finally, our testing revealed an area for improvement in navigation. One clinician participating in our testing referred to a navigation issue on the patient and caregiver Stories page. The clinician said:

I chose to read the transcripts and when I got to the end of the lengthy transcript, I had to scroll all the way to the top to X out of the story.

As a result, the navigation on this page has been amended with the addition of a cancel button or close window option to the bottom of each story, rather than the requirement that users scroll back to the top of the page to close each of the individual stories.

Although we identified areas in which to improve visibility and navigation, our usability testing participants' ability to navigate to the tasks was already excellent. When asked whether they were able to navigate to the pages containing information about lung transplants, the patient and caregiver stories, and the What's Important to Me slider, all clinicians were able to do so. In addition to page navigation, all clinicians were able to complete the What's Important to Me slider and view their results. Finally, 4 of 5 clinicians (80%) were able to find the resources for making an advance directive (Table 4). The patients and surrogates were asked to complete the same tasks. All patients and surrogates participating in our testing were able to find the pages with information about lung transplants, the patient and caregiver stories, and the What's Important to Me slider. All patients and surrogates were also able to complete the What's Important to Me slider. Finally, 6 of the 7 patients and surrogates (86%) were able to find the resources for making an advance directive. Overall, the navigation of the site was easy for the clinicians, patients, and surrogates who participated in usability testing.

Table 4. Task completion exercises.

| Question | Clinicians (n=5), n (%) | Patients and surrogates (n=7), n (%) |
|--|-------------------------|--------------------------------------|
| Navigate to the page containing basic information about lung transplant. Were you able to complete this task? | | |
| Yes | 5 (100) | 7 (100) |
| No | 0 (0) | 0 (0) |
| Find resources for making an advance directive. Were you able to complete this task? | | |
| Yes | 4 (80) | 6 (86) |
| No | 1 (2) | 1 (14) |
| Find the page title "What's Important to Me" for breathing tube. Were you able to complete this task? | | |
| Yes | 5 (100) | 7 (100) |
| No | 0 (0) | 0 (0) |
| Complete the exercise and see your results. Were you able to complete the task? | | |
| Yes | 5 (100) | 7 (100) |
| No | 0 (0) | 0 (0) |
| Find the page containing patient and caregiver stories about intubation and lung transplant. Listen to "Jeff's Story." Were you able to complete this task? | | |
| Yes | 5 (100) | 6 (86) |
| No | 0 (0) | 1 (0) |

Content and Usefulness

Finally, several changes to improve the content and usefulness of CF DA were recommended. One clinician mentioned that patients with CF are often motivated by their desire to survive for their children. Accordingly, we have added the following phrase to the slider: “Seeing my children grow up is important to me” (Figure 5). In addition, as posttransplant pregnancy can pose challenges to both mother and fetus [27], one participant suggested that we include information about alternatives to childbearing, such as adoption and surrogacy, on the Lung Transplant page. The clinician said that in their work settings, they are trying to improve the process of explaining to patients that they:

...can't physically carry [children themselves] but we can have [them] meet with an OBGYN or fertility providers prior to transplant to give [them] the best possible outcomes of having children in some other way or even...counseling about adoption..., surrogacy, different things like that.

These alternative options for becoming a parent have been added to the DA and should address an important emotional aspect of patient decision making (Figure 6).

Discussion

Principal Findings

Although both the clinician and patient and surrogate groups were largely able to complete each of the given tasks, our usability testing sessions revealed several areas for improvement on the CF DA, which we have incorporated. In the functionality theme, suggestions included reordering the content for a more logical flow. In the visibility and navigation theme, optimizations included enlarging the pictures, condensing sections to reduce repetition and improve clarity, visually emphasizing certain features, and adding additional cancel button or close window options to reduce unnecessary scrolling. Suggested improvements to content and usefulness included adding information about adoption and surrogacy for those who wish to become parents following lung transplantation.

In addition to their suggestions for ways to improve the CF DA, participants gave us positive feedback and felt that the DA would be of great benefit to future users. Notably, one of our participants, a surrogate who had children with CF and was also a nurse, said the following:

...I think it's a great tool. I think it's good to have this discussion. Even on my job learning, we talk about lung transplant but it's nice to have something to, you know, to open up the conversation.

One participant pointed to the DA's completeness, describing it as:

Very well done, very clear, hits all important considerations people need to make.

Another participant from the patient and surrogate group stated:

...this website is very informative and it's my belief that it will help a lot of people in the decision-making process.

Therefore, although there was room for improvement, participant responses point toward the future success of the DA in helping patients with CF and clinicians to make informed treatment decisions.

In designing the DA website content, one goal was to facilitate informed decision making via patient or clinician shared decision making. Previous work on informed decision making explores how to best present biomedically based information to ensure that those with low health literacy and numeracy can understand the information being presented. This correctly assumes that an informed decision rests on the individual-level understanding of the information being presented. Various studies have explored language levels (eg, readability should be at the eighth-grade level), and numeric data should be presented to ensure comprehension. Our previous work in DA design has further identified the importance of uptake, that is, the extent to which individuals are able to comprehend information and then apply it to their own decision making. In this way, our work adds to the literature on informed decision making by emphasizing patient-level self-assessment of what makes the patient similar to or different from the data being presented and thereby the extent to which the information is relevant to them. We were concerned with factors that may impact uptake, including previous lived experiences and emotional responses to the information. Therefore, our usability testing questions focused on assessing reactions to the tone of information about end-of-life and advanced CF treatment options. For example, all participants were asked the following survey question: “Was the tone of the information in the decision aid website appropriate?” Importantly, every participant answered “Yes” to this question. Similarly, participants were asked to comment on their reactions to seeing images of an intubated patient. None of the participants indicated emotional distress in their answers, and some even wanted to see the images in more detail. Taken together, participants' overall feedback on the website combined with their responses to these questions eliciting emotional reactions to the website's content indicated that the tone of the website was appropriate and would not elicit emotional responses that would interfere with their ability to comprehend and use the website's content.

Our usability testing needs to be understood within the wider context of our multiphased study to develop and test the InformedChoices CF ACP DA. Beginning with a needs assessment, we sought to design a communication tool that asks people with a lifelong chronic illness to consider their future treatment choices in the event that their illness has progressed to the point at which they need to decide between life-extending treatment and comfort care. As a result, it was essential to assess both the functionality of the DA and individual-level reactions to the content in a controlled setting. Usability testing also allowed us to determine how comfortable clinicians would be accessing and communicating DA content to their patients with CF and how patients would react emotionally to the information before we undertook feasibility and acceptability testing within

the context of an outpatient clinic setting, on a wide scale, across multiple sites.

Next Steps

On the basis of the feedback from the usability testing, we revised the DA. We are currently undertaking multisite feasibility testing of the DA, where we are observing clinicians using it with patients with CF and surrogate caregivers during outpatient clinic visits. Following this, we will make additional revisions before rolling out the DA for use in our clinics and beyond. Our plan is to update the DA regularly as new information and treatments become available, including the survival estimates calculator as survival estimates change, and to add additional patient narratives.

Limitations

One major limitation of our study is that we did not administer the SUS again after revisions were made to the DA. Ideally, we would hope to see an increase in the SUS score after making our changes to the website; however, this was not a part of our study. Another limitation is that we did not test the end user comprehension of the DA. Further analysis of end user response to the DA will be performed as part of a feasibility study in the future. This will consist of observing clinicians, patients, and family caregivers using the DA during 2 ACP conversations in outpatient settings, where we will measure feasibility and acceptability as well as changes in knowledge and decisional conflict over multiple time points. The sample size will also be larger for this phase of our study. Our usability study results are also limited by sample size; however, usability testing is often performed iteratively and with small samples to allow for more in-depth understanding of barriers to use. We are confident that our usability testing sample of 12 participants was large enough for us to obtain substantial feedback, as small sample sizes have been shown to be sufficient to detect most of the

usability issues of a product [26]. However, the small sample size precluded us from performing statistical analyses of our survey response data. Another limitation comes from our highly health literate test population, including clinicians who treat patients with CF and well-informed patients with CF and their surrogates. It is possible that not all of our future end users will be as health literate as our usability testing participants; however, as the DA's end users will be clinicians, patients with CF, and surrogates of patients with CF engaged in shared decision-making conversations, it is highly likely that the opinions of our test population provide an accurate representation of the views of our target audience.

Conclusions

Usability testing helped us identify several areas for improvement of the CF DA. On the basis of user feedback, we have included these changes before implementation of the tool to improve the comprehension, navigation, retention, and overall usefulness of the DA. By integrating participant feedback and making these changes to the CF DA, we hope to improve the site in terms of end user benefits. We expect that these enhancements will lead to higher overall adoption rates of DA by clinicians, patients, and surrogates within our health system. We hope that in the future, this web-based clinical DA tool can be expanded for use in other health systems to help patients with CF and clinicians with ACP and the difficult decisions associated with CF.

Practice Implications

We modified the CF DA based on the user feedback obtained from our usability testing. Integrating changes before implementation should improve the DA's comprehension, navigation, and usefulness. Importantly, this should also lead to a greater adoption of the DA.

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Authors' Contributions

NH, the principal investigator of the study, was responsible for the design of the study, had full access to all of the data, and provided substantial editorial comments to the manuscript. KD contributed substantially to the analysis and interpretation of the quantitative and qualitative data from the study and to the writing of the manuscript. MB contributed substantially to data collection and contributed to the writing of the manuscript. DK contributed substantially to the writing of this manuscript. JP contributed substantially to the data collection. KC, SK, and JS contributed substantially to data analysis and interpretation. DD served as our CF patient partner and contributed to the data collection.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Surveys and measures used as part of the usability testing.

[[DOCX File , 12 KB - humanfactors_v8i2e21270_app1.docx](#)]

Multimedia Appendix 2

The system usability scale. The system usability scale is a 10-item questionnaire with 5 response options: strongly agree (5), agree (4), neither agree nor disagree (3), disagree (2), or strongly disagree (1).

[[DOCX File , 13 KB - humanfactors_v8i2e21270_app2.docx](#)]

Multimedia Appendix 3

Usability task completion exercises.

[[DOCX File , 13 KB - humanfactors_v8i2e21270_app3.docx](#)]

Multimedia Appendix 4

Usability testing survey.

[[DOCX File , 15 KB - humanfactors_v8i2e21270_app4.docx](#)]

Multimedia Appendix 5

Clinicians demographics.

[[DOCX File , 12 KB - humanfactors_v8i2e21270_app5.docx](#)]

Multimedia Appendix 6

Patient and surrogate demographics.

[[DOCX File , 14 KB - humanfactors_v8i2e21270_app6.docx](#)]

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Abbreviations

- ACP:** advance care planning
CF: cystic fibrosis
DA: decision aid
IMV: invasive mechanical ventilation
IPDAS: International Patient Decision Aid Standards
SUS: System Usability Scale

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Original Paper

Comparing Single-Page, Multipage, and Conversational Digital Forms in Health Care: Usability Study

Aleeha Iftikhar¹, MSc; Raymond R Bond¹, BSc, PhD; Victoria McGilligan², BSc, PhD; Stephen J Leslie³, BSc, MBChB, PhD, FRCP; Khaled Rjoob¹, MSc; Charles Knoery³, MBChB; Ciara Quigg⁴, DipNSc; Ryan Campbell⁴, BSN; Kyle Boyd⁵, BSc, MA, PhD; Anne McShane⁶, MSc; Aaron Peace⁴, MRCPE, PhD

¹Computing Engineering and Build Environment, Ulster University, Jordanstown, United Kingdom

²Centre for Personalised Medicine, Ulster University, Londonderry, United Kingdom

³Cardiac Unit, Raigmore Hospital, Inverness, United Kingdom

⁴Department of Cardiology, Altnagelvin Hospital, Western Health and Social Care Trust, Londonderry, United Kingdom

⁵Faculty of Arts, Humanities & Social Sciences, Ulster University, Belfast, United Kingdom

⁶Letterkenny University Hospital, Letterkenny, Ireland

Corresponding Author:

Aleeha Iftikhar, MSc

Computing Engineering and Build Environment

Ulster University

Shore Rd, Newtownabbey

Jordanstown, BT37 0QB

United Kingdom

Phone: 44 07496635353

Email: iftikhar-a1@ulster.ac.uk

Abstract

Background: Even in the era of digital technology, several hospitals still rely on paper-based forms for data entry for patient admission, triage, drug prescriptions, and procedures. Paper-based forms can be quick and convenient to complete but often at the expense of data quality, completeness, sustainability, and automated data analytics. Digital forms can improve data quality by assisting the user when deciding on the appropriate response to certain data inputs (eg, classifying symptoms). Greater data quality via digital form completion not only helps with auditing, service improvement, and patient record keeping but also helps with novel data science and machine learning research. Although digital forms are becoming more prevalent in health care, there is a lack of empirical best practices and guidelines for their design. The study-based hospital had a definite plan to abolish the paper form; hence, it was not necessary to compare the digital forms with the paper form.

Objective: This study aims to assess the usability of three different interactive forms: a single-page digital form (in which all data input is required on one web page), a multipage digital form, and a conversational digital form (a chatbot).

Methods: The three digital forms were developed as candidates to replace the current paper-based form used to record patient referrals to an interventional cardiology department (Cath-Lab) at Altnagelvin Hospital. We recorded usability data in a counterbalanced usability test (60 usability tests: 20 subjects×3 form usability tests). The usability data included task completion times, System Usability Scale (SUS) scores, User Experience Questionnaire data, and data from a postexperiment questionnaire.

Results: We found that the single-page form outperformed the other two digital forms in almost all usability metrics. The mean SUS score for the single-page form was 76 (SD 15.8; $P=.01$) when compared with the multipage form, which had a mean score of 67 (SD 17), and the conversational form attained the lowest scores in usability testing and was the least preferred choice of users, with a mean score of 57 (SD 24). An SUS score of >68 was considered above average. The single-page form achieved the least task completion time compared with the other two digital form styles.

Conclusions: In conclusion, the digital single-page form outperformed the other two forms in almost all usability metrics; it had the least task completion time compared with those of the other two digital forms. Moreover, on answering the open-ended question from the final customized postexperiment questionnaire, the single-page form was the preferred choice.

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KEYWORDS

digital forms; health care; usability evaluation; single-page form; multipage form; conversational forms

Introduction

Background

Currently, when a primary percutaneous coronary intervention (PPCI) referral is made, the nurse activator in the coronary care unit will triage the patient using written notes. Typically, when

a patient experiences chest pain, paramedics arrive and record an electrocardiogram. If the paramedic suspects a heart attack, they will then contact the PPCI department at a hospital and describe the symptoms and electrocardiogram findings to an activator nurse, who then completes a paper form shown in Figure 1 and decides whether patients need to be accepted or turned down.

Figure 1. The current paper-based form being used at Altnagelvin Hospital.

Patient details for pPCI Activation Western Health and Social Care Trust

| | | | | | | | | | | | | | | | | | | | |
|--|--|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--|-----|----------|------|-----|-------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Date: _____/_____/_____ | Time call received: _____ | | | | | | | | | | | | | | | | | | |
| pPCI Activator Name: _____ | Patient name: _____ | | | | | | | | | | | | | | | | | | |
| DOB: _____/_____/_____ | Address: _____ | | | | | | | | | | | | | | | | | | |
| Age: _____ years | Postcode: _____ | | | | | | | | | | | | | | | | | | |
| Referral : please tick: | Referral: please tick: | | | | | | | | | | | | | | | | | | |
| <table border="1"> <tr> <td>NIAS</td> <td>NAS</td> <td>NACC</td> <td>GP</td> </tr> <tr> <td><input type="checkbox"/></td> <td><input type="checkbox"/></td> <td><input type="checkbox"/></td> <td><input type="checkbox"/></td> </tr> </table> | NIAS | NAS | NACC | GP | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <table border="1"> <tr> <td>ALT</td> <td>CAUSEWAY</td> <td>SWAH</td> <td>TCH</td> <td>LETTERKENNY</td> </tr> <tr> <td><input type="checkbox"/></td> <td><input type="checkbox"/></td> <td><input type="checkbox"/></td> <td><input type="checkbox"/></td> <td><input type="checkbox"/></td> </tr> </table> | ALT | CAUSEWAY | SWAH | TCH | LETTERKENNY | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> |
| NIAS | NAS | NACC | GP | | | | | | | | | | | | | | | | |
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| ALT | CAUSEWAY | SWAH | TCH | LETTERKENNY | | | | | | | | | | | | | | | |
| <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | <input type="checkbox"/> | | | | | | | | | | | | | | | |
| CALL SIGN: _____ | H+C NUMBER: _____ | | | | | | | | | | | | | | | | | | |
| INCIDENT NUMBER: _____ | | | | | | | | | | | | | | | | | | | |
| TIME ECG RECEIVED: _____ | ECG FINDINGS: _____ | | | | | | | | | | | | | | | | | | |
| CURRENT COMPLAINT: _____ | BP: _____ Pulse _____ | | | | | | | | | | | | | | | | | | |
| | Saturations: _____ | | | | | | | | | | | | | | | | | | |
| | Temp: _____ | | | | | | | | | | | | | | | | | | |
| Diabetic: Yes <input type="checkbox"/> | | | | | | | | | | | | | | | | | | | |
| No <input type="checkbox"/> | | | | | | | | | | | | | | | | | | | |
| ACCEPTED : | DRUGS: | | | | | | | | | | | | | | | | | | |
| YES: _____ NO: _____ | ASPIRIN 300MGS: _____ TICAGRELOR 180MGS: _____ | | | | | | | | | | | | | | | | | | |
| | Diamorphine: _____ Morphine: _____ | | | | | | | | | | | | | | | | | | |
| CATH LAB : | ETA: | | | | | | | | | | | | | | | | | | |
| 1: _____ 2: _____ | | | | | | | | | | | | | | | | | | | |
| REPAT HOSPITAL: _____ | PAST MED HX: _____ | | | | | | | | | | | | | | | | | | |

This is not unusual, as most hospitals and cardiac care units often rely on paper-based forms for data entry for patient admission or drug prescriptions and other general procedures. Working with paper-based systems can be challenging, especially when a health care staff works in a sensitive and highly stressful environment, such as cardiac care. Digitalization

is slowly being introduced into the health service to improve the medical workflow at different stages and levels. Many applications serve many purposes, including facilitating communication between a patient and a provider, remotely monitoring patients, and measuring population health objectives, such as disease trends. The collected information can be used

to make informed decisions about health care services, either at the population level or individual level, to improve care [1]. Electronic health record (EHR) adoption rates have introduced efficiencies in health care operations, such as instant access to information, improved practice management, and reduced paperwork. Other findings relate to the impacts that EHR systems have on physicians' time, expertise, and learning. The literature also present findings on the impact of EHR systems at the length (and sometimes the accuracy) of the clinical notes [1]. Again, multiple factors contribute to these intrusions, including computer availability, physical positioning of computers, design of the user interface, length of the forms, and procedure of filling the forms. Physician-residents have to use EHR systems because of their mandatory nature; however, if they had a choice or power, most physicians would likely use the paper chart [1]. Recent work has suggested that clinical decision support systems integrated within EHR systems hold the promise of improving health care quality. To date, the effectiveness of clinical decision support systems has been less than expected, especially concerning the ambulatory management of chronic diseases [2]. Nevertheless, although digitization is a drive to improve services, clinicians may not always welcome new digital systems [3]. Certain hurdles may make them reluctant to adopt a digital system, such as prior investment and familiarity with a current system (known as *baby duck syndrome*) [4] and availability, training, and the position of the system [3]. Although it is feasible to use digital forms in medicine, it has its design constraints, including limited display size and the challenge of replicating the user experience of paper forms or checklists [5]. These constraints can be handled; however, there are many conflicting guidelines available on appropriate user-centric designs. Bevan [6] analyzed usability guidelines to inform a user-centric design. Bevan [6] compared these usability methods with those found in textbooks and discussed the most effective way to present user-centric guidelines through a website.

Prior Work

Similar to other fields, digitalization and digital transformation play an essential role in health care. Health care technologies are rapidly growing and evolving; for example, EHR systems are becoming routine [7]. Moreover, different digital forms are being used in medicine in several ways, such as recording triage or referral data, observations of vital signs, and synoptic reporting in pathology. Digital forms and digital checklist systems are computer-based instructions for recording or performing actions as part of managing tasks [6]. Numerous research studies have studied digital forms in medicine,

especially the use of mobile digital forms to support high-quality data collection [8]. It has been stated that electronic reporting is often more efficient and representative with higher rates of data completions [9] and is more effective for supporting clinical decision making. One study stated that using a standard single-page digital form called the standardized outpatient osteopathic note form was more efficient and accurate than the paper-based equivalent [10]. There has been a recent demand for smart checklists (often digital) in medical procedures to reduce iatrogenic or medical errors [11]. A comparison of team performance used a paper checklist with a digital checklist to determine whether digitizing a checklist led to improvements in task completion. The researchers found some improvements in team performance when using the digital checklist [12]. A study developed and evaluated two different versions of a tablet-based cognitive aid to support in-hospital resuscitation team leaders. They suggested that digital cognitive aids may help increase effectiveness and eventually improve patient safety [13]. Chatbots and conversational forms are also being tested in different fields. A comparison of surveys presented as traditional web pages versus chatbot or conversational style surveys (text-based virtual agent) found that participants who used the chatbot style survey produced higher-quality data [14].

Goal

Given the demand for effective digital forms, there is a need to research and discover the best-practice interaction design guidelines for designing digital health forms. In this study, we designed three different digital form styles to replace a paper form that is used for patient referrals to a PPCI service. To contribute to future digital form design guidelines in health care, the study also aims to compare the usability of all three forms to analyze which form styles work best for health care professionals. However, measuring usability is difficult because usability does not refer to a single property; rather, it combines several attributes [15]. According to the standard International Organization for Standardization 9421-11, usability is the effectiveness, efficiency, and satisfaction by which users must achieve a certain goal in a particular environment [16]. This study aims to measure and compare the usability of these three interactive form designs in a counterbalanced experiment in a controlled laboratory at Altnagelvin Hospital.

Methods

Overview

Textbox 1 shows the adopted structure describing the usability test flow for this study.

Textbox 1. Adopted structure describing the usability test flow for this study.

Objective

- The focus or aim is to compare different digital form designs to evaluate which digital form has greater usability.

Participants

- The total study population consisted of 20 health care staff who were either cardiac nurses or research nurses.

Apparatus

- Microsoft surface pro to display the digital forms and to facilitate user interaction, a microphone to record the user's think-aloud data, and screencasting software to video record the user interactions with the digital forms
- Questionnaires (System Usability Scale and User Experience Questionnaire) to measure usability and R-studio for data analysis

Outcomes

- System Usability Scale usability score, usability errors, and task completion times

Procedure

- Counterbalanced experiment to avoid any learning bias
- Typical patient scenarios were presented to the user to facilitate the form completions.

Data analysis

- Summary analysis of System Usability Scale scores, User Experience Questionnaire results, task completion times, error rates using descriptive statistics, and boxplots
- Hypothesis testing (t tests, where $\alpha < .05$) was used to determine statistical significance between System Usability Scale scores and task completion times

Data Set

This study involved the analysis and comparison of three different digital form designs that were developed as candidates for recording patient referrals to a PPCI service at Altnagelvin Hospital (Northern Ireland, the United Kingdom). This study only aims to compare the digital forms, as there are already studies that compare paper forms with digital or electronic forms [17-22]. The paper form was only included to compare the task completion time, and no other metrics were recorded to measure the usability of the paper form. The total study population consisted of 20 health care staff (men: 4/20, 25%; age: 30-39 years) who were either cardiac nurse activators or research nurses. This study included 10 cardiac nurse activators and 10 research nurses.

Development of Digital Forms

The three different digital forms were developed using the HTML 5 and cascading stylesheets (CSS3) following the model view controller paradigm. An open-source scripting library was used to convert the web form into a conversational form [23]. The three digital form designs included (1) a single-page form, (2) a multipage form, and (3) a conversational form (chatbot), as shown in [Figure 2](#), [Figure 3](#), and [Figure 4](#), respectively. The single-page form is where all the input fields are organized and given on a single screen, whereas the multipage form segments the input fields over seven different screens or pages in the form of tabs. In this case, the user completes one page of the form and then navigates to the next tab or section. In the conversational form, the questions are presented to the user in a preset sequence of questions where the user can type in the answer or choose from a series of options. The rationale and expected pros and cons of each type of digital form are presented in [Table 1](#).

Figure 2. Screenshots of a part of the single-page form.

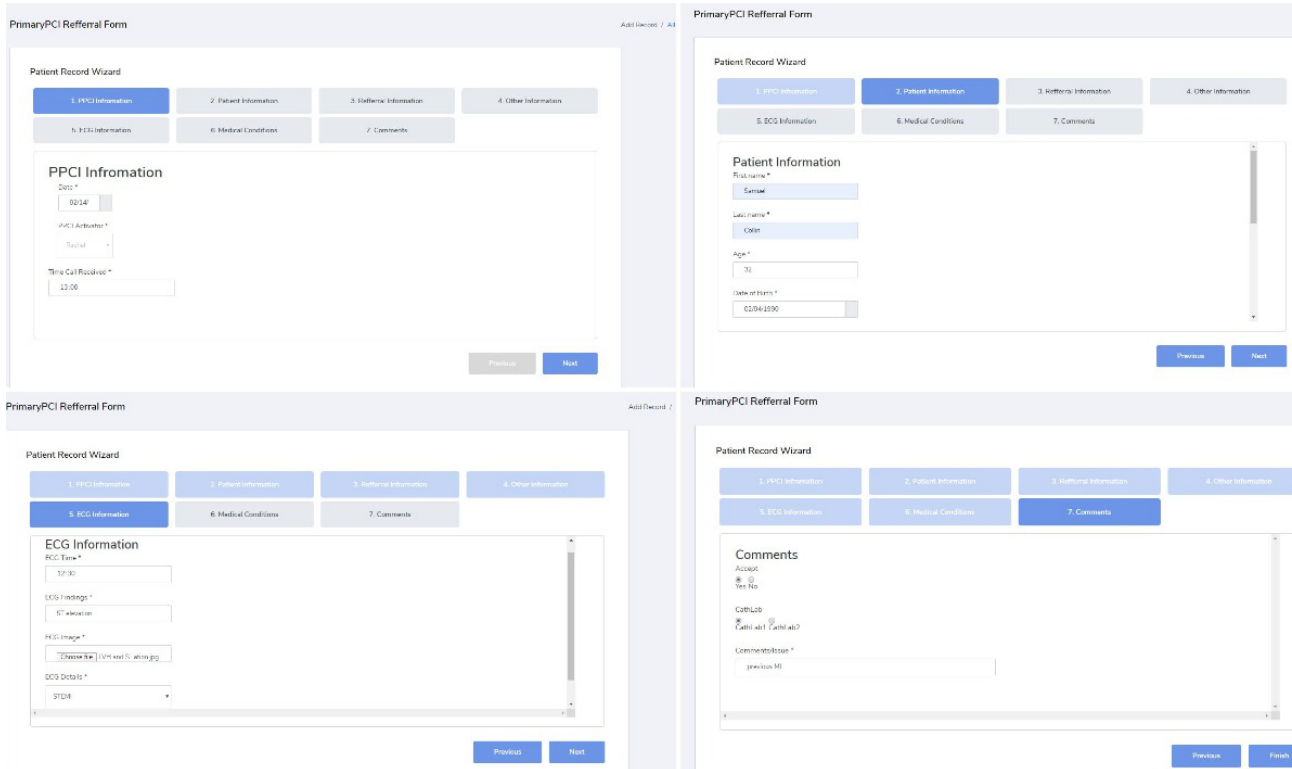


Figure 3. Screenshots of the screens from the multipage form.

Activators Name

Activator Name:

Date:

Time Call Recived:

Call Taken By

Call Sign:

H & C Number:

Incident Number:

Referral:Please Tick
NIAS NAS NACC GP
 Referral:Please Tick
ALT CAUSEWAY SWAH TCH LETTERKENNY

Admittance

Accepted
 Yes
 No

Drugs
 Aspirin 30MGS
 Ticagrelor 180MGS
 Diamorphine
 Morphine

Cath Lab
 One
 Two

ETA

Reptal Hospital

Past Medical History

Any Other Comment/Issue

Patients Name

Name:

Date of Birth:

Age:

Gender
 Male
 Female
 Other

Address:

ECG Details

Time ECG Recieved:

ECG Findings

Current Complaint

Diabetic
 Yes
 No

Figure 4. Screenshots of the conversational form.

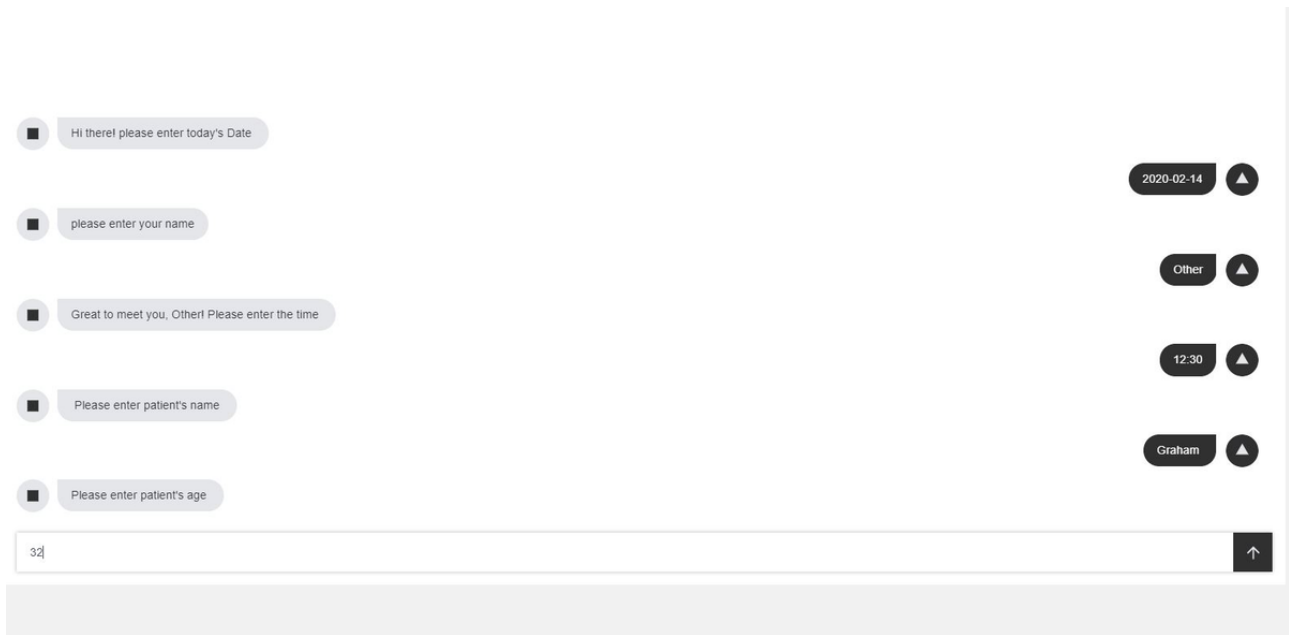


Table 1. Expected pros and cons of the three digital forms.

| Form type | Pros | Cons |
|------------------|--|---|
| Single-page form | <ul style="list-style-type: none"> • Easy to understand • Common form style and meets expectations • User can view all questions and input fields expected of them • User can predict the work required to complete the form • Easy to navigate to all information on a single page | <ul style="list-style-type: none"> • High information rate. Busy looking screen with possible clutter • User can be distracted by the number of questions required • The screen can require more mental workload to interpret • Information overloading can result in visual hierarchy issues |
| Multipage form | <ul style="list-style-type: none"> • Deconstructing a task into subtasks reduces cognitive load • Less distracting for users • User can be guided and focused on a small set of related questions • Creates a sense of progression | <ul style="list-style-type: none"> • Additional interactions (clicks) to navigate to the different sections • Misleads the user into thinking the form is shorter than it is • It might take longer to complete • User needs to navigate to change answers from a previous form subsection |
| Chatbot form | <ul style="list-style-type: none"> • Easy to use • Fewer distractions given only one question is presented per interaction • It is akin to everyday human interaction or to being interviewed and hence engenders focus • Less cognitive demand • It is novel | <ul style="list-style-type: none"> • Not a common form style • Editing previous input could be cumbersome and require a lot of interactions • It seems too playful for formal settings such as medicine • Preset sequence to follow |

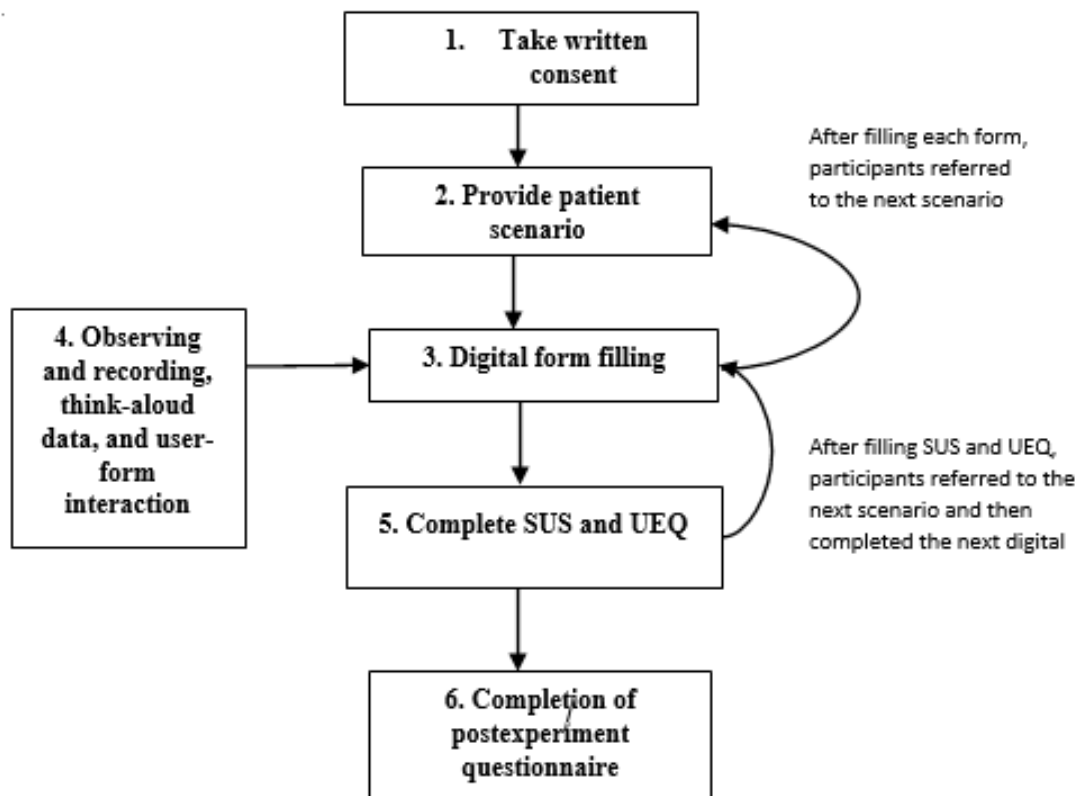
Usability Testing Protocol

The participants identified to be suitable and interested in participating were given a participant information sheet, and written informed consent was obtained from all participants interested in the study (by the author).

This study tested three different digital forms in a simulated setting where each participant was given a brief tutorial on how

to use the tablet PC (Microsoft Surface Pro) that hosted the digital forms. Each participant was provided with the same four PPCI triage-simulated scenarios written on a sheet as shown in [Multimedia Appendix 1](#) and was asked to complete a paper form (standard routine clinical form) and each of the three digital form designs. The sequence of when the subject interacted with the digital forms was counterbalanced to avoid any learning bias. Each session took approximately 60 minutes for each participant. [Figure 5](#) shows the session protocol.

Figure 5. Flowchart depicts the usability testing session flow. SUS: System Usability Scale; UEQ: User Experience Questionnaire.



The researcher observed the participants while they completed the forms, and notes were taken to record usability issues. Form completion was recorded using a screen recording software (FreeScreenRecorder by Screencast-O-Matic [24]) on the tablet. Usability factors were evaluated, including user satisfaction; error rate (error rate was noted while observing the participants filling in the form as well as after the session by watching the recorded video); classification of the severity of the usability issues or error analysis, which was recorded using Nielsen's 4-star severity scale, that is, cosmetic to severe (1-4) [25]; task completion time (each form completion time was noted for each participant using a stopwatch and cross-checked with the video timings); and ease of use (ease of use is a basic concept that describes how easily users can use a product). All questionnaires had questions related to ease of use. Moreover, the error rate and task time also depict the user's ease of using a particular form design. After completing each form, participants were asked to complete the System Usability Scale (SUS) questionnaire [26].

The SUS is commonly used and is a validated questionnaire consisting of 10 items. The scoring of this questionnaire provides a usability score ranging from 0 to 100. An SUS score of >68 is considered above average, and anything <68 is considered below average. A study by Tullis and Stetson [27] performed a comparison of questionnaires for assessing website usability using the Computer System Usability Questionnaire [28]. Brooke [29] developed the SUS in 1996 [29]. The SUS uses a 5-point scale, ranging from strongly agree to strongly disagree. According to Bangor et al [30], the SUS is flexible in assessing a wide range of technologies. The SUS is also

relatively quick and easy to use by study participants. Additionally, the SUS provides a single score on a scale that is easily understood. User experience was also recorded using the standard User Experience Questionnaire (UEQ). The UEQ measures six factors: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty [31]. This questionnaire can be used in different scenarios to record the user experience [32]. The UEQ provides the user with a bidirectional Likert scale with both positive and negative aspects of the system for them to rate, such as questions with positive connotations (easy to learn and creative) and questions with negative connotations (annoying, boring, and not interesting). The questionnaires were completed for all three forms to benchmark and compare the usability of the user interfaces for both positive and negative attributes of each form [33].

A customized postexperiment questionnaire was administered at the end of the session. The postexperiment questionnaire was a final customized researcher-created questionnaire. This questionnaire had 21 usability-related questions that focused more on the needs and types of preferred forms and preferred features.

The recorded data were then analyzed to compare the usability and user experience for each form. This process was used for each subject and also consisted of (1) the concurrent think-aloud protocol and a brief interview, (2) screen recording of the user interactions, and (3) usability evaluation of the final digital form prototypes (60 usability tests: 20 subjects×3 forms). Each participant was observed while they completed each digital

form. The screencast was used to analyze and evaluate the user's behavior.

The data were collected through observations made while the participants were interacting with the digital forms. We then computed the error rate, task completion time, and user satisfaction. For the error rate analysis, a possible error list was made for each form design, and then, the number of errors was noted for each digital form against each user. The least task completion time for a form and the lowest error rate for a particular form can indicate the best form eliciting the highest user satisfaction. User satisfaction was also more explicitly covered in the SUS and UEQ. The postexperimental questionnaire also asked the user about their preferred choice of digital form design.

Data Analysis

Different statistical metrics are used, including median, mean, and SD for the variance. The paired two-tailed *t* test was used to compare any differences between the task or form completion times and the SUS scores between all the three forms. Owing to the multiple statistical tests on the same data sets, Bonferroni corrections were used. Pearson correlation was used to identify any association between the SUS scores and the task completion times. It was not feasible to perform correlation analysis between

other usability factors, such as UEQ answers and error rates, given that they generate categorical results, unlike SUS and the task time, which are numeric values.

Ethical Aspects

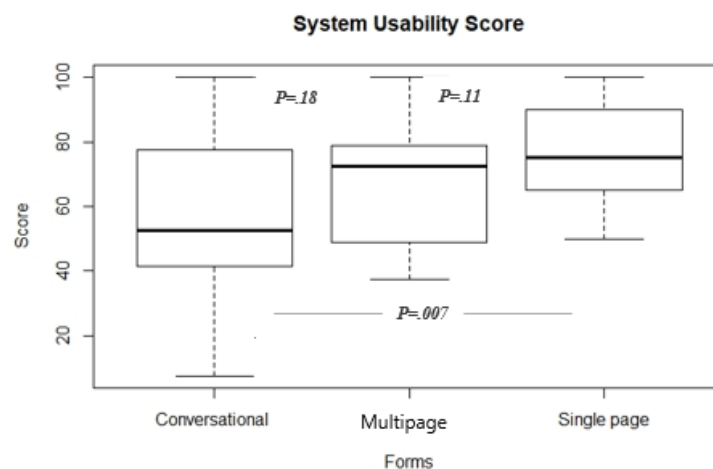
Research governance permission was granted by the Western Health and Social Care Trust (WT 19/08, Integrated Research Application System 262557) and complied with the Declaration of International Research Integrity Association ([Multimedia Appendix 2](#)).

Results

SUS Score Analysis

On the basis of the research, an SUS score of >68 is considered above average [34]. With a mean SUS score of 76 (SD 15), the single-page form outperformed the usability of the multipage and conversational forms. The multipage form was on the borderline with a mean score of 67 (SD 17). The conversational form attained the least scores in the usability testing and it was the least choice of users, with a mean score of 57 (SD 24). The *t* test indicated statistical significance between the conversational and single-page forms. [Figure 6](#) shows a boxplot of the SUS scores for each digital form. Even with the Bonferroni-corrected α value (.015), the results were still statistically significant.

Figure 6. Boxplot for the average System Usability Scale score of each form. The single page had a mean System Usability Scale score of 76 (SD 15) and outperformed the usability of the multipage and conversational forms with mean System Usability Scale scores of 67 (SD 17) and 57 (SD 24), respectively. Even with a β coefficient of .015, the results are still significant.



UEQ Interpretation

The UEQ used in this study was modified from the original version by making it unidirectional and also included the one-sided factors. The single-page form mostly had higher

averages for the positive attributes than the other two digital forms. The conversational form scored higher averages in the negative attributes, which suggests that the conversational form had the least usability. [Figures 7](#) and [8](#) show the mean average ratings for each UEQ question for each digital form.

Figure 7. Bar chart showing positive attribute results of the User Experience Questionnaire for all three forms. The single-page form has higher averages for the positive attributes than those of the other two digital forms.

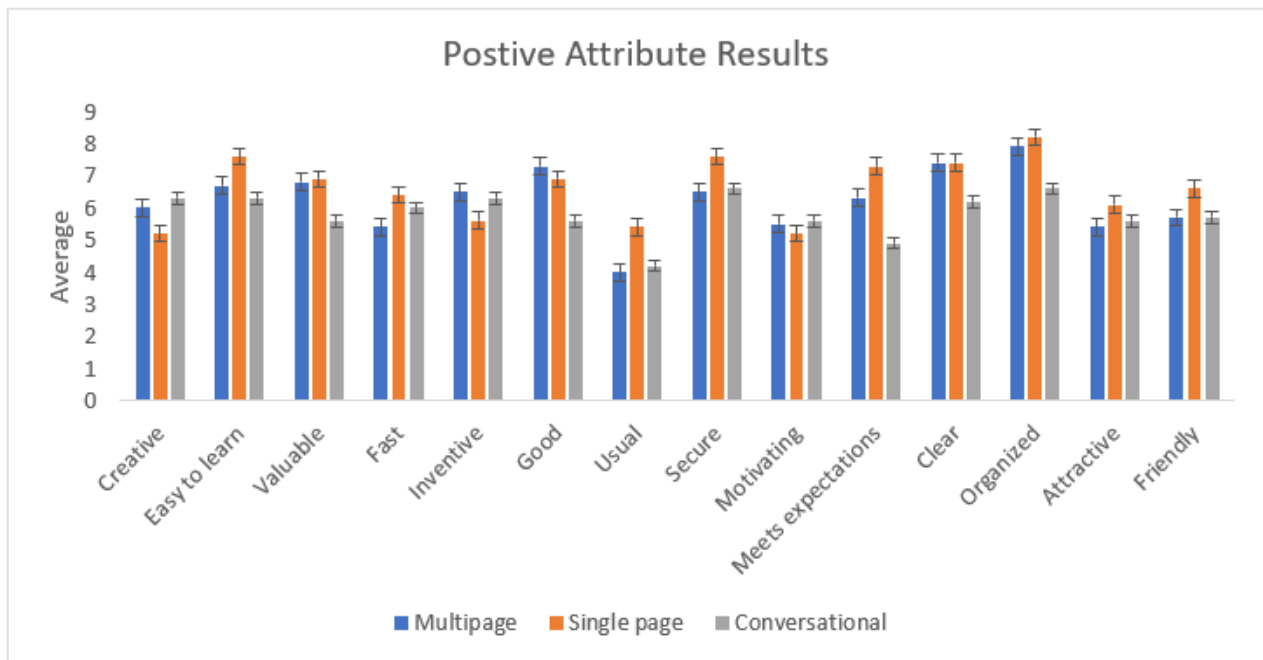
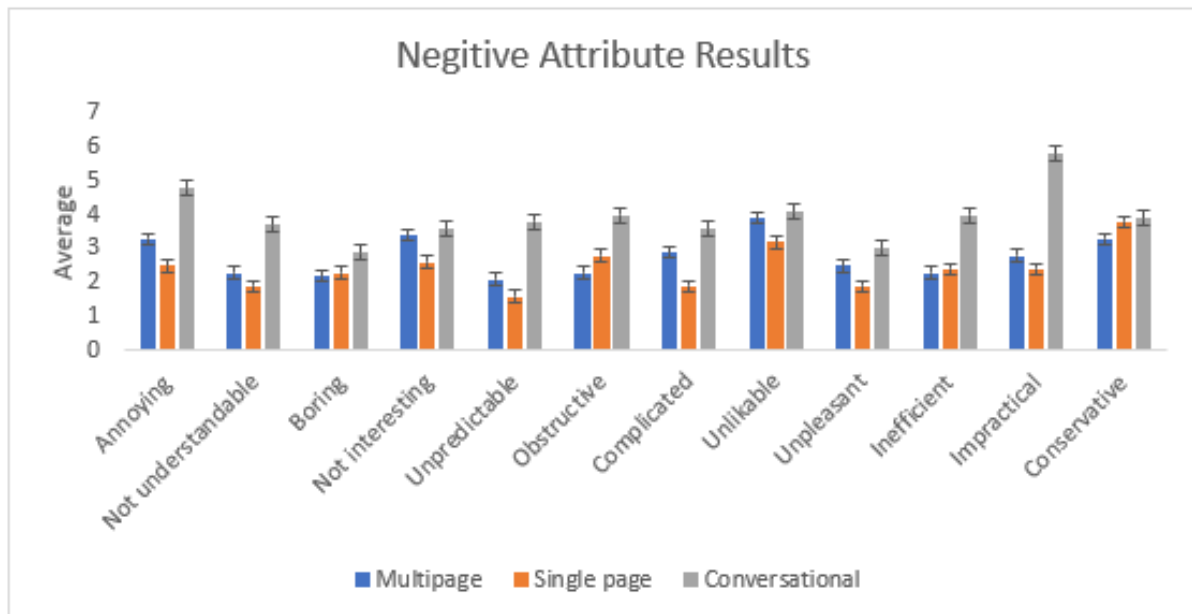


Figure 8. Bar chart showing negative attribute results of the User Experience Questionnaire for all three forms. The conversational form had higher averages for the negative attributes than those of the other two forms, which suggests that the conversational form had the least usability.



Task Time or Form Completion

Task completion refers to the total time a user takes to complete each form. Participants took the least time to complete the paper form. However, the least mean time was recorded for the single-page form, followed by the conversational form among the three digital forms. Users took longer to complete the multipage form. Figure 9 shows a boxplot of task completion times for each form. The PPCI activator nurses took the least time for the paper form, as they are currently using this for PPCI referrals. However, the research nurses who had no prior exposure to this paper form took almost as long as they took to

complete the digital forms (mean 224, SD 54 seconds vs mean 298, SD 60 seconds; $P=.001$).

On the other hand, the activator nurses who took the least time to complete the paper form took almost twice the amount of time to complete the digital form compared with the paper form (165, SD 55 s vs 301, SD 68 s; $P<.001$). The boxplot in Figure 10 shows the mean time of both groups to complete the paper and digital forms. The paired t test is shown in Table 2, where the single-page form shows significance ($P<.001$) with the multipage form and paper form. The multipage form and the conversational form task completion times showed significance ($P<.001$) with the paper form only.

Figure 9. Boxplot for the average form completion time of each form. The primary percutaneous coronary intervention activator nurses took the least time for the paper form, as they are currently using this for primary percutaneous coronary intervention referrals. However, the research nurses who had no prior exposure to this paper form took almost as much time as the time activator nurses took to complete the digital forms (mean 224 seconds, SD 54 seconds vs mean 298, SD 60 seconds; $P < .001$).

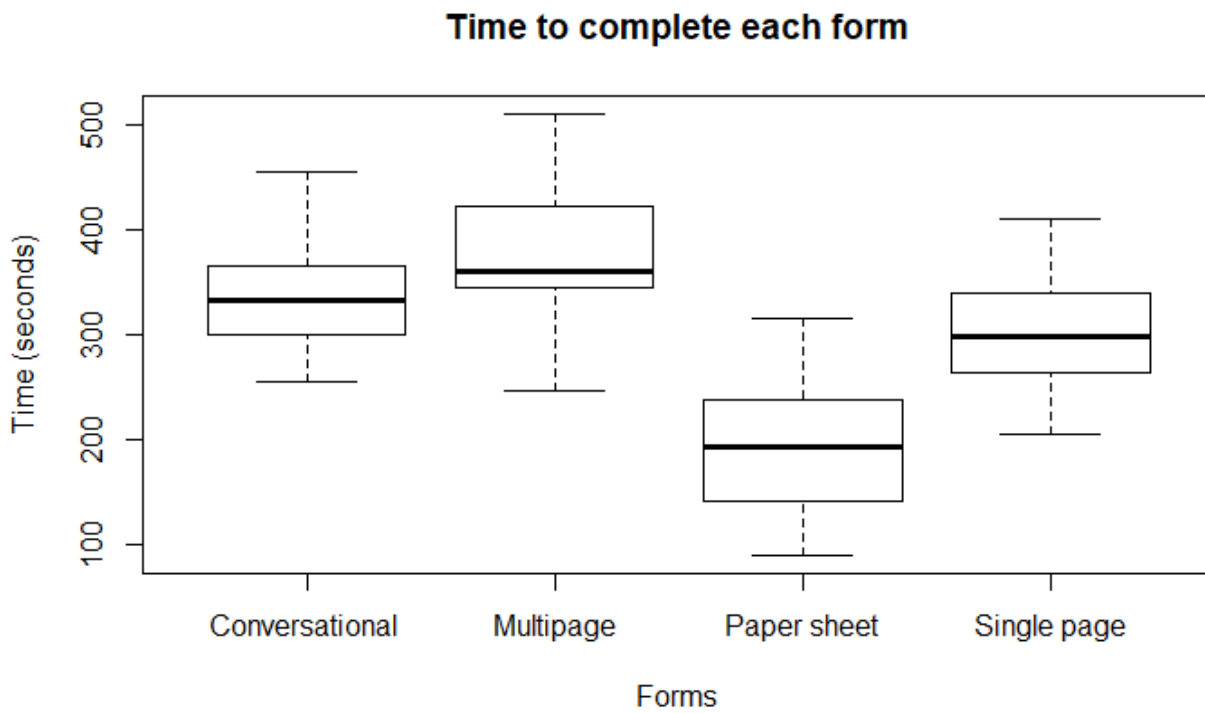


Figure 10. Boxplot for the average form completion time of activators versus research nurses. (A) Activator nurses' form completion time and (B) research nurses' form completion time.

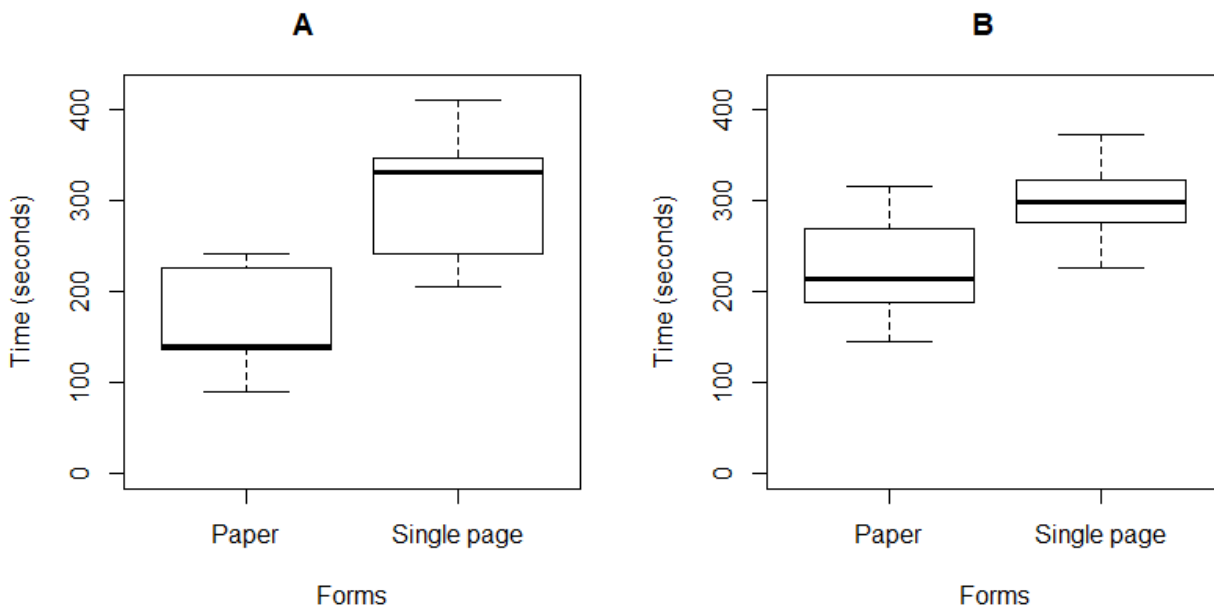


Table 2. *P* values between the completion time of all forms.

| Form comparisons | <i>P</i> value |
|--|----------------|
| Single-page form and multipage form | <.001 |
| Single-page form and conversational form | .02 |
| Single-page form and paper sheet | <.001 |
| Multipage form and conversational form | .10 |
| Multipage form and paper sheet | <.001 |
| Conversational form and paper sheet | <.001 |

Correlation: SUS Score and Task Time

There was a weak correlation ($r=-0.28$) between the SUS score and form completion time (Figure 11). This shows that task

completion time alone does not measure the usability of a system. Figure 12 shows the scatterplot for the overall correlation between the SUS score and each form completion time.

Figure 11. Scatterplot for the overall correlation between the System Usability Scale score and task completion time. There was a weak correlation ($r=-0.28$) between the System Usability Scale score and form completion times. This shows that the task completion time alone does not measure the usability of a system. SUS: System Usability Scale.

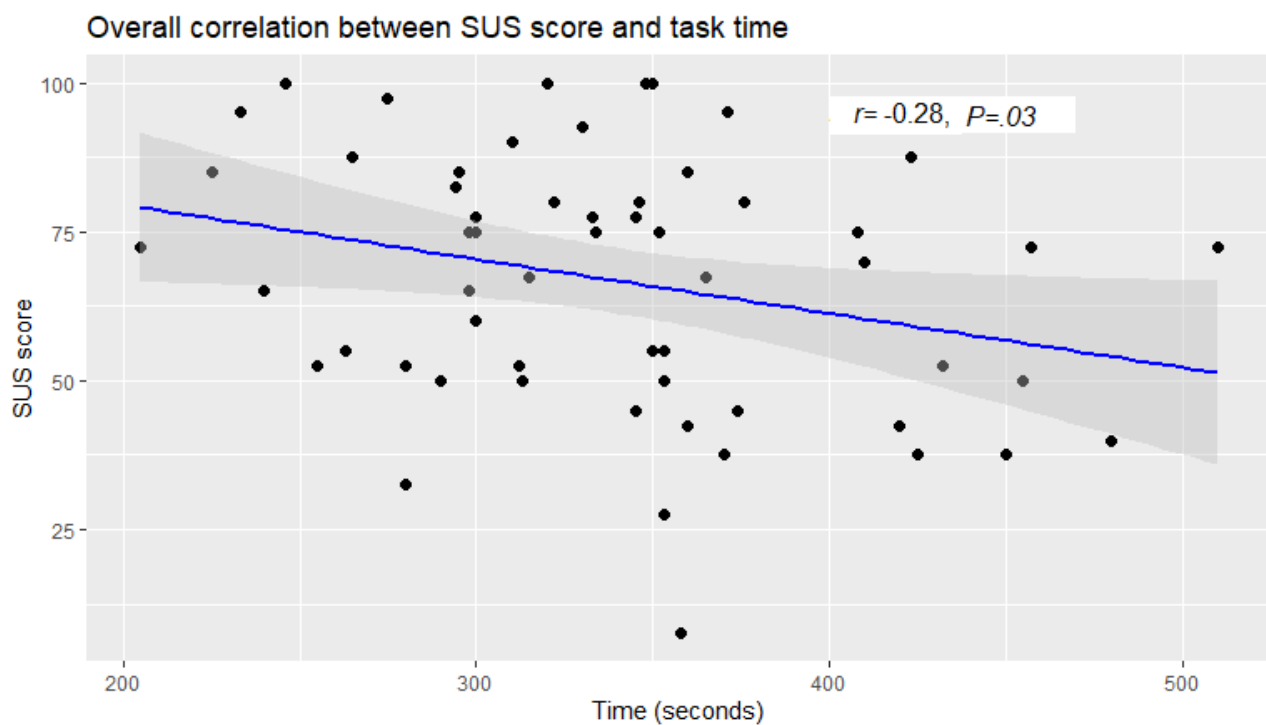
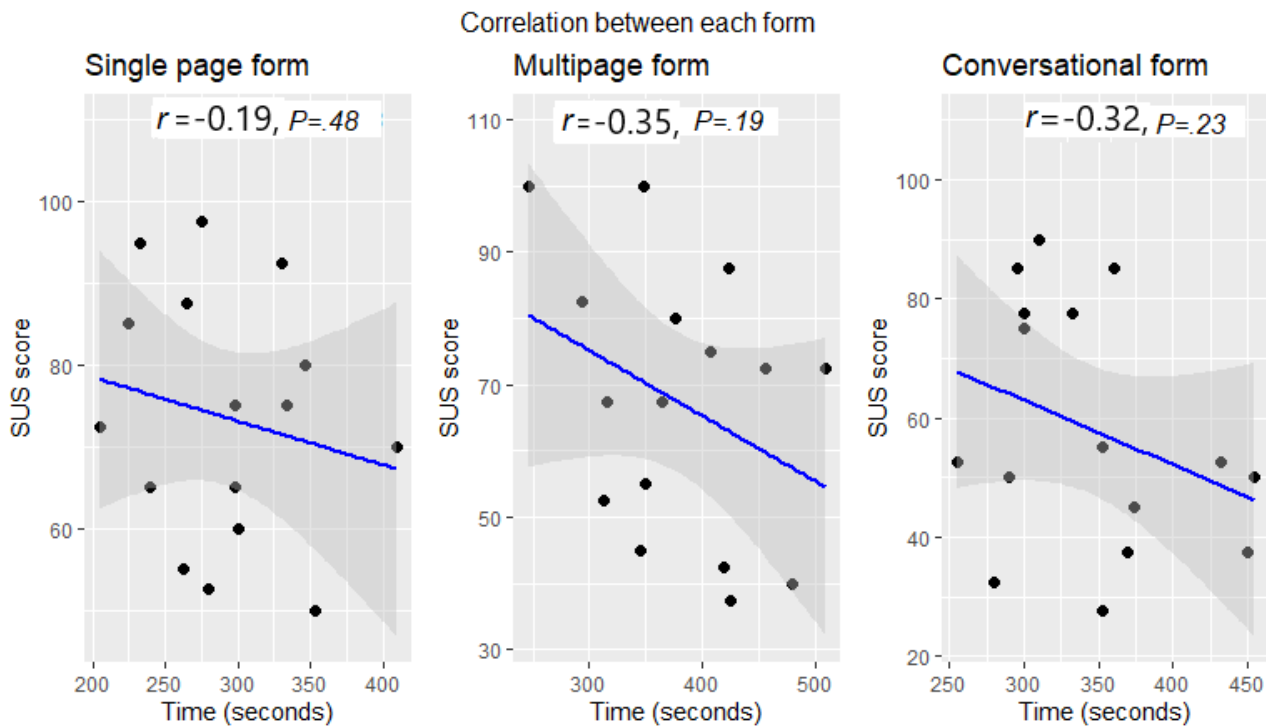


Figure 12. Scatterplot for the overall correlation between the System Usability Scale score and each form's completion time. SUS: System Usability Scale.



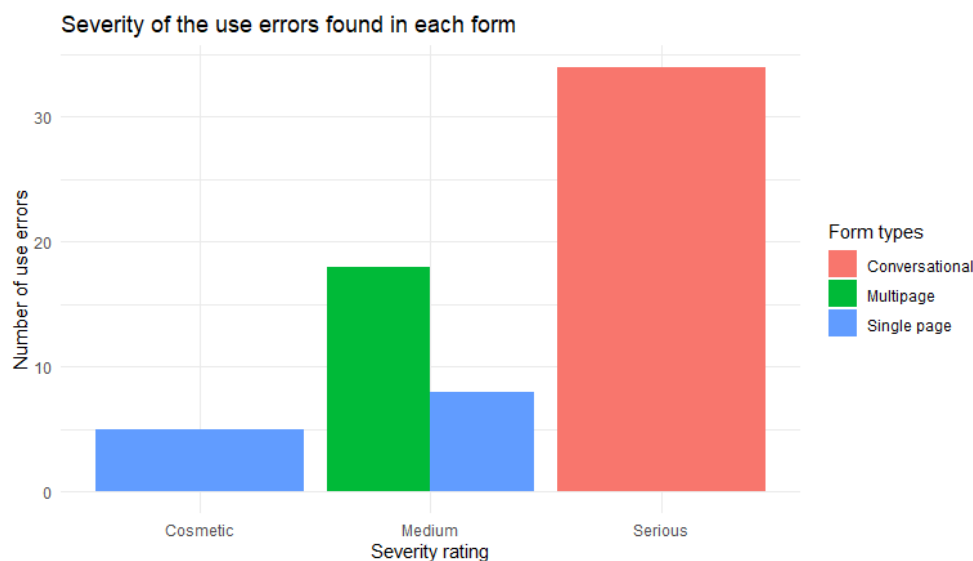
Error Rate and Classification

Upon inspection of the video screen recordings, the use errors and their frequency were recorded. A use error can have 1 of 4 severity ratings according to Neilsen’s 4-star severity scale, that is, cosmetic, medium, serious, or critical. There were no critical use errors; however, there were many serious use errors in the conversational form. The multipage form errors were 69% medium errors, whereas the single-page form had only 31%

medium errors and very few cosmetic errors. Figure 13 shows a bar graph of the error severity of each form.

On the basis of this usability study, approximately 83 use errors (average severity 3.0) were discovered in the conversational form, 35 use errors (average severity 2.0, SD 0) were discovered in the multipage form, and 21 use errors (average severity 1.76, SD 0.44) were discovered in the single-page form. The severity of these use errors is shown in Figure 13.

Figure 13. Bar graph for each form’s error severity. The multipage form errors were 69% medium errors, whereas the single-page form had only 31% medium errors and very few cosmetic errors.



Postexperiment Questionnaire

Approximately half of the participants preferred the single-page form. In response to an open-ended question, the users

mentioned that the single page was “easy to complete,” “easy to understand,” “well-marked and separated,” and “clearer” and that “all the information is available to see at once.” For the multipage form, the users said the “entire information isn’t

available” and that they “don’t like to navigate.” For the conversational form, the users said that it was “unpredictable” and “difficult to understand and use” and that they “couldn’t go back easily to the options if they need to or want to.”

Discussion

Principal Findings

This study has shown that a single-page digital form outperformed the multipage and conversational forms while performing usability evaluation for the three digital forms designed for PPCI referrals to better understand the usability needs of nurses. This is an interesting finding, as the conversational form was previously used successfully to aid in different areas [35,36]. In terms of task completion times, the single-page form achieved the minimum completion time, followed by the conversational form.

The correlation analysis between the SUS score and task time showed no strong relationship, indicating that task completion time alone cannot measure the usability of a system. All the standard usability metrics considered in this research concluded that the single-page digital form performed better than the multipage and conversational forms. Moreover, while answering an open-ended question in the final questionnaire, more than half of the participants chose the single-page form as their preferred choice. Some of the reasons for preferring the single-page form were that it is easy to complete, easy to understand, well-marked and separated, clear, and all the information is available to see on one screen. For the multipage form, participants did not seem to like navigating between the pages. For the conversational form, participants found it more unpredictable; difficult to understand and use; and, most importantly, to be unable to conveniently go back to change data inputted if they needed to.

Usability assessment and appropriate form design or form design guidelines are vital for health care departments. For form filling in health care, if the form is not well designed, people will have to think harder to complete it. If they think harder, it means they will take longer to fill in the form, so they could miss information or skip it or even enter wrong information. If people take long time to fill the forms, it takes them away from the actual patient care. If they make mistakes and put in wrong information, any algorithms, data analysis, or dashboards that use those data would be wrong. Clinical strategies and decision making at the board level or hospital level based on those data would be wrong because a nurse had not completed a digital form properly. The fact that the digital form is being used routinely and at a high frequency makes their usability crucial because you will think that a system as simple as a form should not require a high mental workload. It should be as intuitive and as simple as possible. A digital form impacts algorithm development and policy decision making because much of the data are based on policy decision making, which means that if data are wrong, then the policies are also wrong. If people are not putting in the right data, then policy decisions will be faulty as well. In this day and age, we make many decisions based on the data, so data can be either new oil or a new snake oil if the data are misleading or wrong. Data are substantial if it is correct,

but it can lead to bad decisions if data are not correct. The results from the study clearly show that a single page form has better usability overall than its multipage and conversational form counterparts. This has implications for form design moving forward but, in many ways, reinforces good user experience design guidelines when it comes to form design [37]. By using single-page forms, they allow the layout to be simplified and make a form easily scannable. When people first see a form, they will perceive how long it will take for them to complete it by scanning the form. Therefore, perception does play a role. The more complex it looks, the more likely people will abandon the process. There is also the interaction cost or the *reservoir of goodwill*. Filling in web forms represents a sum of effort both cognitively and physically that people must put in when interacting with a web form to reach a goal. The more effort required, the less usable the form is. The reservoir of goodwill diminishes, and people abandon the process; single-page forms allow long forms to appear smaller by minimizing the number of fields that are seen at the same time. This creates the perception that the form is shorter than it really is. This is done via progressive disclosure, showing just what the people need on the screen at the right time. By also *chunking* breaking the form into steps allows people to process, understand, and complete information in a small portion at a time. The trend for web forms is this approach with web builders, such as Google forms [38] and typeform [39], using this approach.

Limitations

The digital forms were trialed at only one hospital with a small group of health care professionals, and the usability results may differ at other centers. However, the ethical approval board is in the process of including another hospital site in the study to increase the number of participants. The study was conducted in a simulated scenario in which the location and patient presentation were simulated. Perhaps in real scenarios, participants would be under more pressure (eg, time pressure). Usability data were not recorded for the paper version. No usability data are available for the paper form, as the usability questionnaires (SUS and UEQ) are designed to assess digital interfaces. Paper forms are what health care staff are very familiar with and might bias any comparisons made. For example, they have already adopted paper systems and have become experts in paper form filling. Hence, it can be argued that it is unfair to compare paper form completion with digital form completion because this compares expert use with novice use. Moreover, another key limitation is that perhaps single-page digital forms are preferred because that format is also widely used and users might have already become familiar with these form styles.

Future Work

How will people complete digital forms in the future? This is an interesting question, especially in the era of artificial intelligence. Perhaps there will be more intelligent smart speakers that will be used for completing forms, for example, an artificial intelligence algorithm that listens to the patient’s details and completes the form using natural language understanding. However, talking to a computer requires more

effort than selecting options in a form. Further research is required to explore these ideas.

Conclusions

In conclusion, the digital single-page form outperformed the other two forms in almost all usability metrics. The mean SUS score for a single page was 76 (SD 15), with the least task completion time when compared with the other two digital

forms. Moreover, on answering the open-ended question, the single-page form was also the preferred choice. However, this preference might change over time as multipage and conversational forms become more common. For example, the conversational form's SUS scores achieved a greater variance, indicating a possible dichotomy among participants regarding the perceived usability and usefulness of chatbot style form.

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Authors' Contributions

All of the authors were responsible for study conception; the design, analysis, and interpretation of results; and the revision of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Simulated patient scenarios provided for form filling.

[[PDF File \(Adobe PDF File\), 87 KB - humanfactors_v8i2e25787_app1.pdf](#)]

Multimedia Appendix 2

Ethical approval certificate/letter.

[[PDF File \(Adobe PDF File\), 295 KB - humanfactors_v8i2e25787_app2.pdf](#)]

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Abbreviations

EHR: electronic health record

PPCI: primary percutaneous coronary intervention

SUS: System Usability Scale

UEQ: User Experience Questionnaire

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Original Paper

Sex Differences in Electronic Health Record Navigation Strategies: Secondary Data Analysis

Daniel R Seifer¹, MD; Karess Mcgrath¹, MSc; Gretchen Scholl², BSc; Vishnu Mohan¹, MD; Jeffrey A Gold¹, MD

¹Division of Pulmonary and Critical Care Medicine, Oregon Health & Science University, Portland, OR, United States

²Department of Medical Informatics and Clinical Epidemiology, Oregon Health & Science University, Portland, OR, United States

Corresponding Author:

Jeffrey A Gold, MD

Division of Pulmonary and Critical Care Medicine

Oregon Health & Science University

3181 SW Sam Jackson Park Rd

Portland, OR, 97239

United States

Phone: 1 5034181496

Email: goldje@ohsu.edu

Abstract

Background: Use of electronic health records (EHRs) has increased dramatically over the past decade. Their widespread adoption has been plagued with numerous complaints about usability, with subsequent impacts on patient safety and provider well-being. Data in other fields suggest biological sex impacts basic patterns of navigation in electronic media.

Objective: This study aimed to determine whether biological sex impacted physicians' navigational strategies while using EHRs.

Methods: This is a secondary analysis of a prior study where physicians were given verbal and written signout, and then, while being monitored with an eye tracker, were asked to review a simulated record in our institution's EHR system, which contained 14 patient safety items. Afterward, the number of safety items recognized was recorded.

Results: A total of 93 physicians (female: n=46, male: n=47) participated in the study. Two gaze patterns were identified: one characterized more so by saccadic ("scanning") eye movements and the other characterized more so by longer fixations ("staring"). Female physicians were more likely to use the scanning pattern; they had a shorter mean fixation duration ($P=.005$), traveled more distance per minute of screen time ($P=.03$), had more saccades per minute of screen time ($P=.02$), and had longer periods of saccadic movement ($P=.03$). The average proportion of time spent staring compared to scanning (the Gaze Index [GI]) across all participants was approximately 3:1. Females were more likely than males to have a GI value <3.0 ($P=.003$). At the extremes, males were more likely to have a GI value >5 , while females were more likely to have a GI value <1 . Differences in navigational strategy had no impact on task performance.

Conclusions: Females and males demonstrate fundamentally different navigational strategies while navigating the EHR. This has potentially significant impacts for usability testing in EHR training and design. Further studies are needed to determine if the detected differences in gaze patterns produce meaningful differences in cognitive load while using EHRs.

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KEYWORDS

eye tracking; electronic health record; gaze; usability; sex differences

Introduction

In the last two decades, the percentage of physicians using an electronic health record (EHR) in their practice has risen from around 10% to over 80%, driven in varying degrees by federal initiatives, intra- and internetwork pressure, and perceived potential advantages. This increase represents a broad shift in

practice patterns that have introduced new challenges into the process of delivering quality medical care. Though EHRs come with many benefits such as improved compliance with clinical guidelines, substantial decreases in medication errors, the ability to improve care through simulation, and increased cost-savings at an institutional level, the development and implementation of the EHR has far outpaced investigation into their downsides

[1-5]. It is clear that the amount of documentation required per patient has increased substantially with the advent and implementation of EHR systems [6]. Interface design, usability, and interoperability issues have plagued EHRs since their initial iteration in the 1970s; increased documentation and input requirements correlate with increased error rates, longer hospital stays, less job satisfaction, and physician burnout [7-10]. Tools for understanding the usability patterns of EHRs are sorely needed in order to better inform system design and provider training.

The user experience of any type of electronic system such as an EHR depends entirely around the ways in which the user navigates the system to produce desired outcomes; an eminently capable program will be useless if users cannot utilize its capabilities. Appropriately then, interface navigability is a consideration at the forefront of electronic system design. Of course, humans did not evolve with electronic system navigation as an active evolutionary pressure; instead, the human brain is optimized for spatial navigation. There are two recognized spatial navigation strategies: (1) local landmark usage and (2) distant cues (eg, cardinal directions) utilization [11]. All neurotypical humans are capable of utilizing either strategy when required by a given situation; however, individuals have a reliable tendency by default to one strategy over the other, and sex is a strong predictor of one's default strategy [11-15]. In these spatial tasks, females tend to default to using local landmarks while males default to utilizing distal cues. Although social expectations can have an effect on task performance, the phenomenon of default strategy selection appears to be strongly influenced by genetic and hormonal factors rather than socialization [16-19].

Analogous sex differences in navigational strategy have also been observed in the varied contexts of navigating electronic screens. Females reported higher utilization of situation-specific navigational cues during single-site hypertextual (ie, website) navigation and more frequently used landmarks to guide others verbally when acting as instructors [20]. Previous work showed that performance on text-based database querying tasks (eg, Google, PubMed, etc) improves with increased content knowledge across both sexes; however, no matter the level of content knowledge, elementary-school-aged females spent more time reading documents, formulated fewer overall queries, and clicked on fewer links per minute than their male counterparts, although none of these measures correlated with overall task performance [21]. Constrained to a search task in an area of low-domain knowledge, middle-school-aged males and females showed no differences in performance in nonelectronic library searches but did show a difference in task performance when using the web, a finding which has been replicated [22,23]. Finally, differences in gaze patterns during the higher-level analytical tasks of C-program debugging correlated with task performance [24,25].

Only a handful of studies have investigated eye tracking with regard to EHR usage with the majority focused on EHR use as opposed to characterizing user characteristics [26-28]. Previously, our group used eye tracking to characterize general features of gaze in hospital physicians and found that there were two distinct workflows: while all participating physicians spent

far more time writing their notes than perusing the chart overall, one group of physicians perused the chart at length before opening their notes while the other started their notes immediately. This difference in workflow was associated with physician sex in that females physicians were more likely to peruse the chart before starting their notes [29]. Though no sex-related performance differences in medical diagnostic reasoning have been reported thus far, these results showed that differences in EHR navigation do exist between female and male physicians. While the impact of sex differences on EHR navigation remains unknown, what is apparent is that the increase in EHR use nationally has correlated with a dramatic increase in physician burnout that is increasingly being recognized as disproportionately affecting female physicians [9,10,30].

Simulation affords a powerful tool to better understand the role of sex in EHR navigation by removing the variability inherent in analyzing deidentified patient charts and replacing it with a standardized, validated case that is the same for all participants. We have previously reported the use of high-fidelity EHR-based simulation to understand error recognition in simulated intensive care unit (ICU) charts [28,31-33]. In these preliminary studies, we incorporated eye and screen tracking to determine whether gaze metrics could be used as surrogates for EHR performance. We demonstrated that a number of eye-tracking metrics correlated with the recognition of embedded safety items within the chart for the entire cohort. The goals of this study were twofold: (1) to expand upon the initial data set in order to analyze whether sex was associated with differential navigation patterns during simulated EHR exercises, and (2) to determine the impact, if any, this difference had on task performance.

Methods

This study was approved by the Institutional Review Board at Oregon Health & Science University. The study was deemed minimal risk, and formal informed consent was not required. However, all participants were provided with an information sheet on our research protocol.

Physicians' eye movements were recorded with a Tobii X1 monitor-mounted Light Eye Tracker (Tobii Systems) while completing a previously validated EHR-based simulation exercise in our EHR environment (EpicCare, Epic Systems Inc) [4,33]. This simulated instance imported all end-user settings, preferences, and customized screens so that participants were able to use their own personalized data gathering tools. We created 2 simulated ICU patients, each admitted to the ICU for 5 days. We attempted to make the simulated patient scenarios as robust as possible, with hourly vital signs, lab results, and nursing, as well as resident and attending notes. Residents and fellows rotating through the medical ICU were eligible for enrollment, and thus all had experience with the use of the EHR in the context of the exercise they were being asked to complete. Participants were provided a written "signout" and then given 10 minutes to review data on one of the simulation cases, with instructions to review the EHR as if they were assuming care for the patient and would be presenting them on rounds, along with any potential changes in management that would be

required for their care. At the end of 10 minutes, participants then presented the care plan for the patient to a member of the study team. The participants' performance was assessed by the number of safety issues they verbalized during this presentation, followed by a debriefing of the safety issues associated with the case as previously described [4,31,32]. The physical nature of the computer station used for the testing was standardized by fixing monitor, desk, and chair height, as well as tilt and relative positioning of the monitor at 65 cm from the participant. Calibration was performed for each subject using a 1-minute-long, 9-point calibration algorithm provided by the manufacturer.

Once complete, all videos were captured and analyzed with the vendor's eye-tracking software (Tobii Studio, Tobii Systems). Fixations were defined as a period (>60 milliseconds) in which providers' eyes tracked without eye velocity exceeding 30 degrees/second. Saccades (rapid scanning eye movements) were defined as periods with gaze velocity exceeding 30 degrees/second, these definitions being adapted from current standards within the literature [34]. Static eye tracking on points for <60 milliseconds were termed "microfixations," as they did not meet broadly acceptable standards for the fixations referenced above. These were present primarily while participants were retrospectively observed to be reading blocks of full sentences. Raw tracking data was analyzed using custom Excel macros designed to calculate more complex variables (eg, screen distance between fixation points, fixation duration, etc). Variable distribution was analyzed in GraphPad (GraphPad Software Inc). Many of the recorded variables were definitionally bounded on the low end producing one-tailed variable distributions. Given these distributions, appropriate nonparametric tests were used to assess for differences between group means.

Krejtz et al [35] introduced coefficient K, seeking to construct a single, trackable indicator of fluctuation between ambient or focal eye movements. This metric was designed to track gaze patterns across visual stimuli (eg, art, visual stimulation tasks,

etc), and their reported results are promising; however, it was not suitable for answering the question posed in our work, given that we sought to differentiate between two active self-driven data extraction strategies ("scanning" vs "staring"), which requires a variable built to purpose [35]. We thus developed a novel variable—the Gaze Index (GI)—to denote the ratio of time spent in long fixation ("staring") to time spent in saccadic motion ("scanning"). The GI represents the proportion of time each participant spent in fixation versus saccade. For example, a GI of 0.11 would indicate that a participant spent approximately 9 times more of their screen time in saccade-microfixation-saccade-etc (a "reading"/"scanning" pattern) than in full fixation ("staring"). It inherently normalizes for the time each participant spent viewing the screen, making the GI a superior representation of participant behavior when compared to the raw ratio of fixations to saccades. Normalization to screen time is particularly important given the top-bounded nature of saccadic movement compared with the unbounded upper limit of fixation periods, which could easily skew results based on the finite nature of this time-constrained task.

For analysis, we correlated individual usability measures to performance on the simulation. Differences in performance between groups with specific usability characteristics were compared using a Mann-Whitney *U* Test based on the size of the data set and the nonparametric nature of the data. Normality was assessed via Kolmogorov-Smirnov. All analyses were performed using GraphPad Prism (GraphPad Software Inc), and a *P* value of <.05 was considered statistically significant.

Results

The data set comprised the eye-tracking recordings of 93 physicians (female: *n*=46, male: *n*=47). Of these, 39 (42%) were interns; the remaining were in their PGY (postgraduate year) 2 year and above. None of the recordings were excluded from analysis. Self-supplied specialty identifications were similar between groups (Table 1).

Table 1. Demographics of study participants (N=93).

| Specialty | Females (n=46), n (%) | Males (n=47), n (%) |
|---------------------------|-----------------------|---------------------|
| Internal Medicine | 34 (74) | 32 (68) |
| Anesthesia | 3 (7) | 3 (6) |
| Pulmonary & Critical Care | 3 (7) | 2 (4) |
| Critical Care | 3 (7) | 3 (6) |
| Emergency Medicine | 1 (2) | 2 (4) |
| Neurology | 1 (2) | 0 (0) |
| Unspecified | 1 (2) | 5 (11) |

Overall, females spent less task time looking at the screen than males (44.7% vs 55.1%; *P*=.007, *U*=767) (Figure 1).

While looking at the screen, the mean fixation ("stare") duration of all participants was 212 milliseconds, which is in line with previously reported mean fixation durations during text-reading tasks [36]. No difference was found in the number of fixations per minute between females and males (mean 191.3, SD 5.1 vs

mean 189.7, SD 3.9) (Figure 2A); however, the mean fixation duration was shorter for females than males (mean 197.6, SD 7.2 vs mean 226, SD 6.6 milliseconds; *P*=.005, *U*=740) (Figure 2B). Finally, there was a trend toward an increase in the mean distance traveled between fixations among females (mean 195.7, SD 5.1 pixels vs mean 184.6, SD 4.5 pixels; *P*=.07, *U*=892) (Figure 2C).

We next analyzed saccadic (“scanning”) eye movements. Females traveled more distance per minute of screen time (35,026, SD 1065 pixels per minute vs 33,542, SD 943 pixels per minute; $P=.03$, $U=839$) (Figure 3A) and had more saccades per minute of screen time (347, SD 18 vs 288, SD 16; $P=.02$, $U=817$) (Figure 3B). Furthermore, their periods of saccadic movement were of longer duration (63.1, SD 2.4 milliseconds vs 56.4, SD 1.8 milliseconds; $P=.03$, $U=836$) (Figure 3C). In total, female physicians scanned more often and for longer durations than their male counterparts.

In order to investigate the relative time spent between fixation and saccadic movement, we calculated GI values for all subjects. The GI had a wide frequency distribution across all participants (0.11-7.02). The mean GI of all participants was approximately a 3:1 ratio, indicating that the participants, on average, spent 3 times as much of their screen time staring as they did scanning: 46 participants had a GI value >3.0 , while 47 participants had a GI value <3.0 (Figure 4).

We termed those users with a $GI>3$ “starkers” and those with $GI<3$ “scanners” to qualify their tendency toward either eye movement relative to the average GI of 3. Interestingly, females were more likely than males to have a $GI<3.0$ (2.4 vs 3.4; $P=.004$, $U=739$) (Figure 5A). When looking at GI extremes, males were more likely to have a $GI>5$ (odds ratio [OR] 4.51 vs OR 0.22) while females were more likely to have a $GI<1$ (OR 1.58 vs OR 0.63) (Figure 5B). No differences between specialties were detected either in pooled analysis or in analysis within sex groups (not shown).

Lastly, we sought to determine whether differences in navigation patterns predicted performance in the simulation. Overall, there were no appreciable differences between females and males in task performance measured by percentage of existing safety items identified (39.9, SD 16% vs 38.6, SD 19%; $P=.97$) (Figure 6). Similarly, when users were grouped by their differences in GI rather than by sex ($GI<1$ vs $GI>5$; $GI<3$ vs $GI>3$) there were no detectable differences in task performance (not shown).

Figure 1. Comparison of percent task time spent looking at the screen between female and male physicians. Each subject is represented by an individual point with the error bars representing mean (SD).

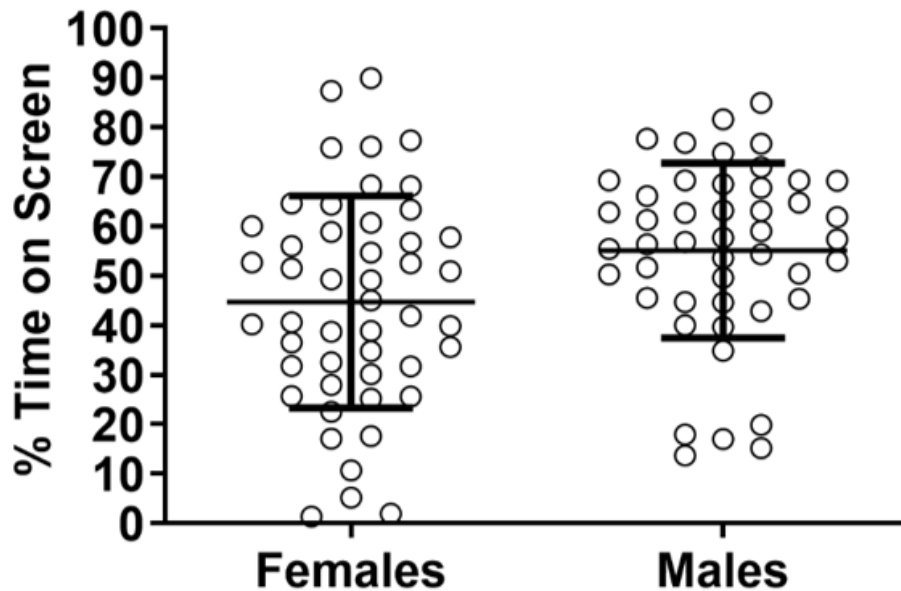


Figure 2. Comparison of fixation data metrics between female and male physicians. (A) There was no difference in the number of fixations recorded per minute of screen time. (B) Female physicians had a significantly lower mean fixation duration than their male colleagues. (C) There was a trend toward female physicians traveling a longer distance between fixation points. Error bars represent mean (SD).

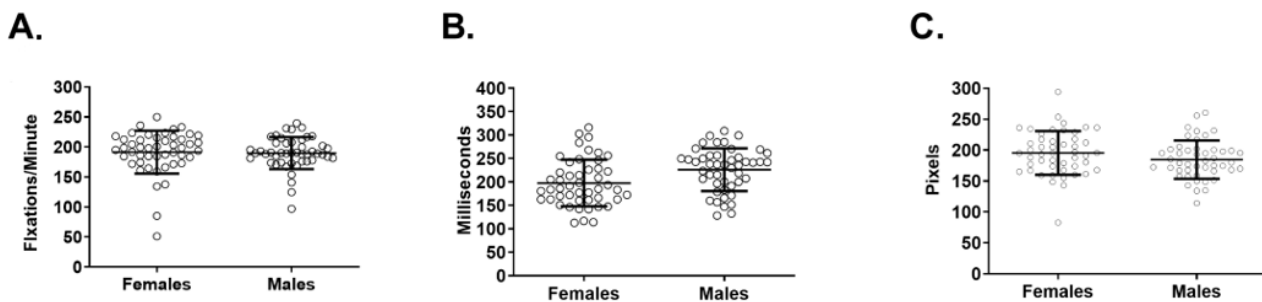


Figure 3. Comparison of saccade metrics between female and male physicians. (A) Female physicians traveled more screen distance per minute of saccadic movement than their male colleagues. (B) Per minute of screen time, female physicians had more, separate, and distinguishable periods of saccadic movement than their male colleagues. (C) The saccadic periods of female physicians were also significantly longer than those of their male peers. Error bars represent mean (SD).

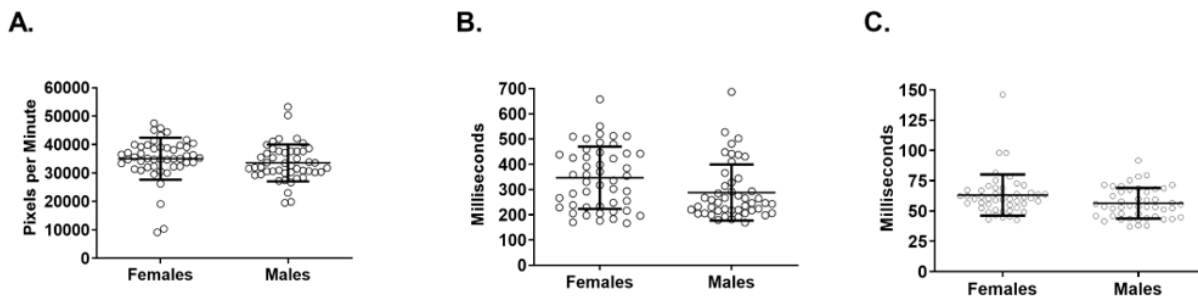


Figure 4. Plot of the Gaze Index (GI) of all participants. The mean GI of all participants was approximately a 3:1 ratio, indicating that the participants, on average, spent 3 times as much of their screen time staring as they did scanning: 46 participants had a GI value >3.0, while 47 participants had a GI value <3.0. Error bars represent mean (SD).

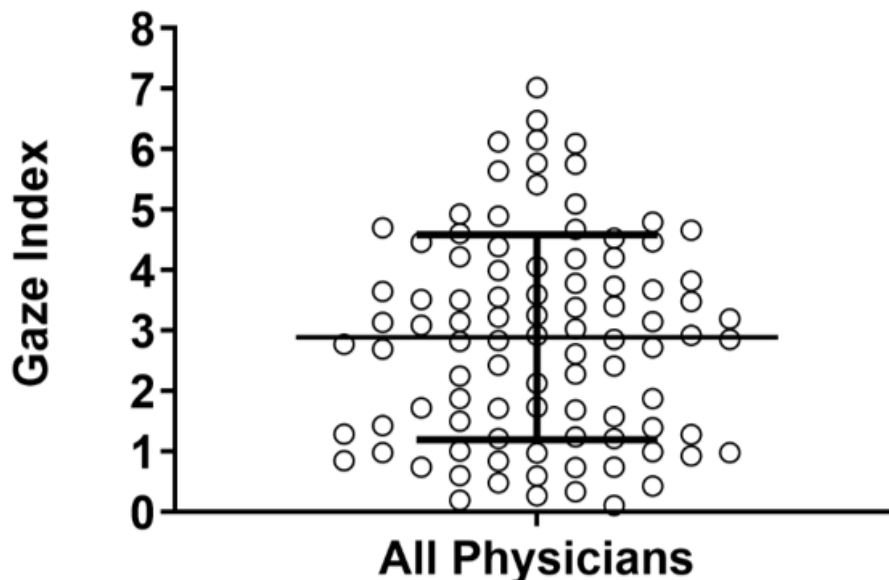


Figure 5. Comparison of the Gaze Index (GI) of female and male physicians. (A) The GI differed significantly between female and male physicians with the former having a group average of <3 and the latter having a group average of >3. (B) “Superstarers” (those with a GI>5, closed circles) were disproportionately male (odds ratio [OR] 0.22 vs OR 4.51), while “superscanners” (those with a GI<1, open circles) were disproportionately female (OR 1.58 vs OR 0.63). Error bars represent mean (SD).

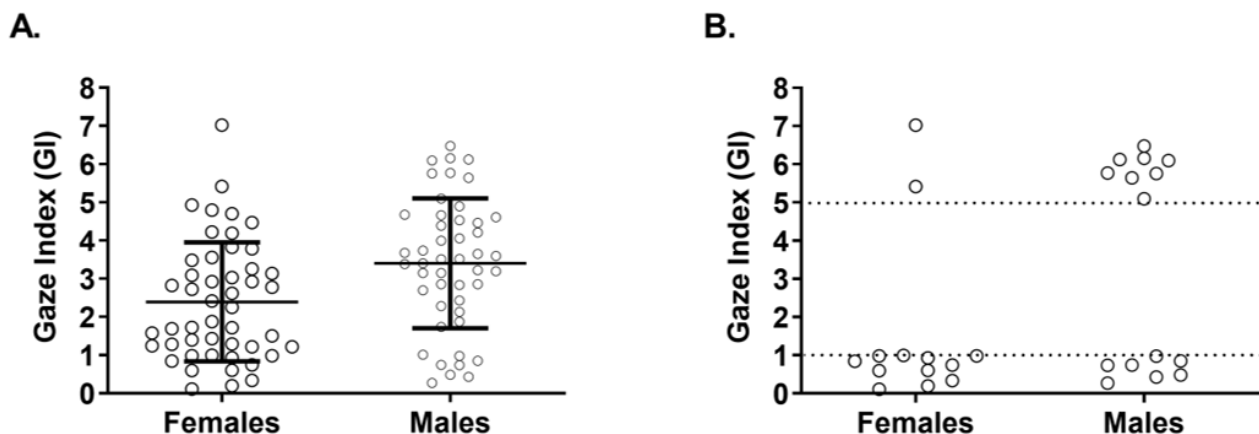
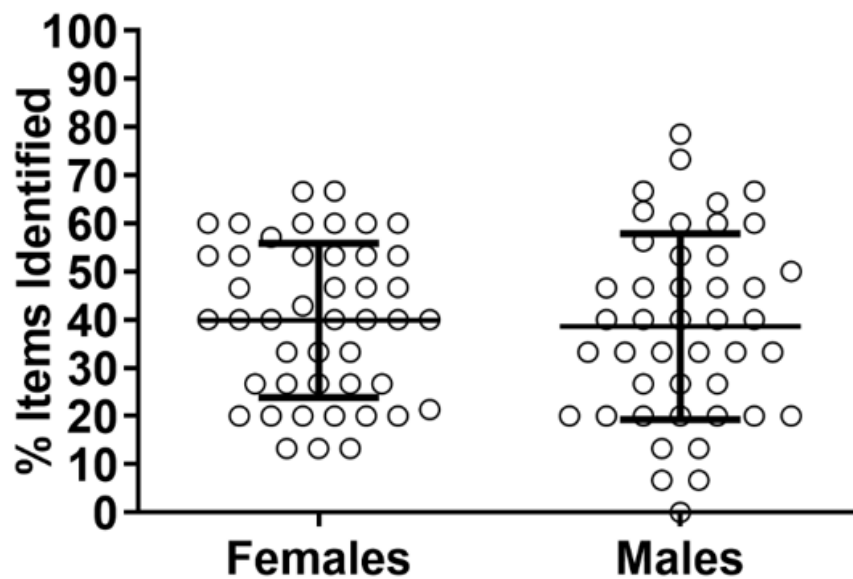


Figure 6. Comparison of task performance between female and male physicians; no difference was detected. Error bars represent mean (SD).



Discussion

Principal Findings

This study characterized the eye movements of physicians as they completed a previously validated simulation of prerounding data collection, and showed that physician sex was associated with distinctly different patterns of eye movements while reviewing the EHR. Female physicians tended to scan the medical chart for both proportionally longer amounts of time and more frequently than their male colleagues. By contrast, male physicians spent more of their EHR task time staring at points of interest for longer periods. No other variable was correlated with physician GI, and neither physician sex nor any gaze metric, including the GI, was predictive of task performance.

Scanning (saccades) and staring (fixations) are inextricably linked in gaze mechanics. One cannot scan indefinitely and still process information nor can one fixate indefinitely if they wish to move between points of interest. As such, a focus on either type of movement alone would not fully characterize the overall gaze pattern. For example, a high number of saccades per minute coupled with a high number of short fixations (as is seen while reading text) would be a completely different pattern than a high number of saccades per minute coupled with a smaller number of longer fixations (as is seen while perusing quantitative charts). Similarly, a simple ratio of the absolute number of fixations divided by the absolute number of saccades would be inadequate to describe a gaze pattern as the duration of both movement portions would not be incorporated into this ratio. For the purposes of correlative analysis then, a single variable taking into account both movement types and their respective durations is required. In this study, the GI served this purpose and allowed us to assess whether overall gaze pattern is associated with any other outcome such as task performance.

Our finding that sex is predictive of differences in physician GI during EHR usage is consistent with work in other navigatory domains—both spatial and electronic [11-15,20-22,25]. When viewed as a whole, the work done in this area supports that sex-linked navigational differences are global and have at least part of their roots in biology as opposed to being solely linked to socialization or environmental cues [17-19]. A GI of <3 is descriptive of a scanning pattern of EHR analysis, examples of which may include reading text in notes, sequentially scanning the entirety of a flowsheet, etc. This gaze pattern is even more strongly represented in those physicians with $GI < 1$, a group predominantly female. In contrast, a GI value of >3 describes a fixation-focused pattern of EHR analysis inconsistent with text reading and more consistent with a longer examination of fixed data points without reading the sheet in entirety; this is even more true of those with a $GI > 5$, who were overwhelmingly male. Our finding that female physicians' eye movements represented greater screen distance per time than their male counterparts while they maintained the same absolute number of fixations per time also supports this characterization of female gaze patterns as consistent with linear, sequential scanning.

Our findings thus align with the differences between the sexes observed in the spatial realm where females default to scanning local landmarks for orientation while males default to fixating on distant orienting points. The stronger sorting of strategies by sex in the spatial realm is likely due to the fact that biology evolved to deal with this distinction in spatial orienting, whereas we are detecting the impact of this default spatial navigatory preference filtered through an entirely different domain (ie, the EHR). Given this difference, it is remarkable that the effects of this navigatory default are seen so strongly in the physicians in our study. That the physicians in our study still sort robustly by the GI according to sex while navigating the EHR, an artificially constructed environment full of literally thousands of data points that require years of education in order to place in context,

speaks to the foundational level of this navigatory difference between females and males.

Despite the significant difference in GI between the sexes, we saw no difference in task performance between females and males overall. No correlation was found between the GI and task performance either overall or at the extremes. This is not a completely unexpected finding. While differences in default navigatory strategies are associated with significant performance differences in spatial navigation tasks, there is more variance in the types and the extent of performance differences exhibited in various types of electronic navigation as in this study [12]. This is likely in part due to the fact that biologic differences would have evolved due to evolutionary pressure from spatial orientation tasks. In addition, there is also the question of the ability to control for confounding variables in the task. Spatial navigation tasks are basic and do not involve higher cognitive reasoning processes; however, the same cannot be said of medical analysis tasks, which integrate cognition and navigatory skills. The task assigned to our subjects involved significant parsing of standardized, simulated ICU patient data, and, as such, diagnostic reasoning is inextricably tied to the eventual task score even though the cases themselves are the same between participants. In line with task load principles, with increasing task difficulty, one by definition will see load (cognitive and/or physical) increase before performance decreases. Therefore, it is plausible that successful completion of the task only partially depended on electronic navigation and may not have been focused or challenging enough to elicit a performance decrease.

Limitations

One important limitation to this study is that we only measured performance as determined by task completion without assessing the cognitive load and stress incurred during the task. Indeed, this may be the more important metric for future studies given the association of EHR use with burnout and job dissatisfaction. This is especially important given the number of studies that suggest significant differences in metrics potentially related to the EHR between female and male physicians, with female physicians reporting more compassion fatigue, double the rate of burnout, lower job satisfaction, lower pay for comparable work, a larger increase in suicide rate from the baseline population as compared to their male colleagues, and increased time pressure during their work [37-41].

Our study had a variety of other limiting features apart from the inability to measure cognitive load and stress. Given the secondary analysis of the study, we did not capture all other

potential sociotechnical confounders such as prior EHR experience from the subjects. As such, our ability to assess whether other variables of a social or environmental nature were also associated with the GI was limited. Perhaps most significantly, the task the physicians performed was not optimized for the detection of eye-tracking variables and introduced a number of unnecessary steps between navigation and scoring given its focus on oral presentations. Physicians spent significant time looking away from their screen to their written notes or the provided signout, which limited the amount of eye tracking performed. Our outcome measure being orally reported data points meant that oral presentation skills, recall, and even handwritten data organization were all introduced as unnecessary confounding variables. While these task limitations may have increased our chance of type II error with regard to detection of a relationship between the GI and task score, we do not expect that they would have increased the chance of type I error with regard to the detected difference in GI between females and males. Finally, while all subjects had some experience with EHRs and specifically were familiar with its use in the context of the activity being simulated, we do not have other demographic information on the subjects such as age, total years of experience with the institution's specific EHR system, and experience with other forms of electronic data interfaces. Thus, we cannot fully exclude these as additional factors that may serve to confound the observed findings; this highlights the need to further confirm these findings in a dedicated, prospective evaluation with a dedicated assessment of these domains.

Conclusions

In conclusion, the results of our study presented here, specifically differences in GI, total screen distance traveled, individual saccadic period duration, individual fixation duration, etc, support the conclusion that, as a group, female physicians are more likely to scan longer, more often, and more broadly while male physicians are more likely to fixate on particular areas of interest. Demonstrated differences in GI and other eye-tracking metrics are similar to those seen in other electronic navigatory tasks in which gaze type maps with performance, and also similar to eye movement differences seen in spatial navigatory tasks. This association is concerning as it raises the possibility that physicians of one sex may be disproportionately impacted by design considerations of the EHR interface in a manner that potentially cannot be corrected with end-user training or mitigated over time with increasing familiarity of EHR use.

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Conflicts of Interest

None declared.

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Abbreviations

EHR: electronic health record

GI: Gaze Index

ICU: intensive care unit

OR: odds ratio

PGY: postgraduate year

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Original Paper

Mapping the Psychosocialcultural Aspects of Healthcare Professionals' Information Security Practices: Systematic Mapping Study

Prosper Kandabongee Yeng¹, MSc; Adam Szekeres¹, PhD; Bian Yang¹, PhD; Einar Arthur Snekkenes¹, PhD

Department of Information Security and Communication Technology, Norwegian University of Science and Technology, Gjøvik, Norway

Corresponding Author:

Prosper Kandabongee Yeng, MSc
Department of Information Security and Communication Technology
Norwegian University of Science and Technology
Teknologivegen 22
Gjøvik
Norway
Phone: 47 61135400
Email: prosper.yeng@ntnu.no

Abstract

Background: Data breaches in health care are on the rise, emphasizing the need for a holistic approach to mitigation efforts.

Objective: The purpose of this study was to develop a comprehensive framework for modeling and analyzing health care professionals' information security practices related to their individual characteristics, such as their psychological, social, and cultural traits.

Methods: The study area was a hospital setting under an ongoing project called the Healthcare Security Practice Analysis, Modeling, and Incentivization (HSPAMI) project. A literature review was conducted for relevant theories and information security practices. The theories and security practices were used to develop an ontology and a comprehensive framework consisting of psychological, social, cultural, and demographic variables.

Results: In the review, a number of psychological, social, and cultural theories were identified, including the health belief model, protection motivation theory, theory of planned behavior, and social control theory, in addition to some social demographic variables, to form a comprehensive set of health care professionals' characteristics. Furthermore, an ontology was developed from these theories to systematically organize the concepts. The framework, called the psychosociocultural (PSC) framework, was then developed from the various combined psychological and sociocultural attributes of the ontology. The Human Aspect of Information Security Questionnaire was adopted as a comprehensive tool for gathering staff security practices as mediating variables in the framework.

Conclusions: Data breaches occur often in health care today. This frequency has been attributed to the lack of experience of health care professionals in information security, the lack of development of conscious care security practices, and the lack of motivation to incentivize health care professionals. The frequent data breaches in health care threaten the mutual trust between health care professionals and patients, which implicitly impacts the quality of the health care service. The modeling and analysis of health care professionals' security practices can be conducted with the PSC framework by combining methods of statistical survey, observations, and interviews in relation to PSC variables, such as perceptions (perceived benefits, perceived threats, and perceived barriers) or psychological traits, social factors, cultural factors, and social demographics.

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KEYWORDS

information security; psychological; sociocultural; health care professionals

Introduction

Background

Data breaches in health care are on the rise, emphasizing the need for a holistic approach to risk mitigation. According to IBM's 2019 report [1], the cost of data breaches in the health care sector has remained the highest among all other sectors for the past 9 years. As of 2019, health care organizations registered the highest cost of data breaches (approximately US \$6.5 million), which was 60% more than the cost reported by other industries [1]. Moreover, cyberattacks in health care are believed to represent a global phenomenon. In 2018, through the aid of a staff member, the health care records of about half the total population of Norway (3 million) were compromised [2]. The attack, which was considered as one of the biggest data breaches to have occurred in Norway, was described as a targeted method to access patient data at the Health South East Hospital. As a result, Norwegian citizens wondered whether health care data controllers were adopting reliable measures to secure the massive amount of sensitive health information collected from patients. In another incident, according to HealthCare IT News [3,4], a phishing attack compromised 38,000 patient records from Legacy Health based in Portland, Oregon in the United States. Personal data, such as patients' email accounts, demographic information, dates of birth, health insurance data, billing details, medical data, social security numbers, and driver's license information, were stolen. In a similar incident [3,4], about 1.5 million patient records, including data of the prime minister of Singapore, were breached. It was noted that the cybercriminals began by compromising front-end workstations, giving the attackers access to privileged user credentials. The attackers then escalated privileges to obtain access to the database. The breached data included demographic information, patient identification numbers, and medical information, such as diagnoses and test results. In the United States, about 365 breaches were reported in 2018, and hacking was the leading cause of health care data breaches, followed by other unauthorized access and disclosure incidents [5].

The use of information technology (IT) in health care (like in other sectors) has become indispensable [6]. Electronic health records now have multiple connections to health care professionals, patients, insurers, devices, and researchers [6]. The multiple points of access available to a larger number of stakeholders translates to multiple entry points and an increased attack surface. Additionally, health care professionals are usually busy with their core roles of restoring patients' health, so little attention remains for focusing on information security [7,8]. Information security is instead often ignored to allow health care professionals to focus heavily on patients' timely health restoration, especially in emergency care situations. This trade-off creates opportunities for adversaries to attack and gain access to health care systems [7,9-11].

Perimeter defenses have long been the default mechanism for providing information and network security and have therefore matured over the years. Perimeter defenses refer to securing the boundary between a company's intranet and the public network (the internet) with physical security systems and technological

countermeasures, such as firewalls, intrusion detection and prevention systems, security policy configurations, and antivirus systems [12]. Penetration through these perimeter measures is deemed more difficult and requires significant resources. Hackers therefore turn to explore easy entry points. With humans being the most vulnerable link in the security chain, attackers tend to exploit the human element to gain access to systems [13,14].

The health care context is characterized by high levels of trust between various social and peer groups [14-16]. This trust exists largely due to the identification of health care personnel through their professional training and socialization process [8]. Additionally, all health care practitioners typically value confidentiality as a result of the ethical principles and oaths, such as the Hippocratic Oath, that are core elements in health care professions [14-16]. This social and cultural bonding of health care professionals was identified as problematic for information security [14-16]. Health care professionals' practices can also deliberately or inadvertently cause internal security breaches [3,14-17]. Furthermore, health care professionals have subtle variant behaviors in the usage of information communication technology in health care, which can threaten the confidentiality, integrity, and availability of personal health information [15,18,19]. The model of confidentiality, integrity, and availability is an information security model, which was developed to provide guidance for developing security policies to meet the availability, integrity, and confidentiality requirements of the assets of organizations [15,18,19]. Various researchers found that two-thirds of employees have contributed to data breaches [14-16,20] through mistakes or deliberate actions.

Security issues in health care have serious consequences [7,21,22]. Besides the potential loss of dignity, patients' suffering may range from fraud to patient injury or death in health care-related data breaches [4,8,23,24]. Hospitals also experience a loss of trust and confidence from patients and other users if they experience data breaches. When hospital operations are interrupted, the cost of recovery from breaches is very high, especially in hacking related to ransomware [25,26]. Health care organizations can also face stringent sanctions from regulatory bodies, such as the General Data Protection Regulation (GDPR), or as a result of violating the Health Insurance Portability and Accountability Act (HIPAA) [24,27]. Violations of privacy and security regulations, such as the GDPR, by organizations in Europe could result in fines up to 4% of their annual global turnover or 20 million euros [28]. According to the International Organization for Standardization (ISO), the annual estimated losses from cybercrime could reach US \$2 trillion in the near future, with countless daily additions of new breaches [29].

To this end, there is a need to assess the security practices of the human element in order to control data breaches in health care. Good security practices have been defined in regulations, policies, standards, guidelines, and codes of conduct, which are required to be implemented with both technical and nontechnical measures. However, to what extent do users comply with the established security policies? What are the challenges often faced by health care workers in their effort to comply with the

prescribed security practices while doing their work? Are these security measures in conflict with the health care professionals' health-related practices? How can the security requirements be improved for effective compliance while improving security effectiveness? How can health care workers be incentivized to better comply with security requirements while conducting their primary work? To protect the very sensitive nature of health care data, the health care domain needs to be properly modeled, assessed, and analyzed from the perspective of all possible entry points to mitigate attacks that are often associated with the psychological, social, cultural, and demographic characteristics of system users [30]. We therefore developed a comprehensive framework to uncover security issues caused by the human element termed in this paper as "health care professionals' security practices." This paper has been organized as follows. The *Theoretical Background* section provides details of the project, theories, and security practices used in the study, while the *Methods* section describes our adopted method. This is followed by a presentation of the results, followed by discussion of the results.

Theoretical Background: Psychosociocultural Context

Amid the increasing frequency of data breaches in health care, all possible methods that can be used to model and analyze health care professionals' security activities for security metrics should be considered. To this end, the Healthcare Security Practice Analysis, Modeling, and Incentivization (HSPAMI) project was introduced to model and analyze the security practices of health care professionals with the objective of assessing the gap between required security practices and current health care security practices [12]. The findings will support the development of solutions or incentives to improve health care professionals' security behaviors.

The security practices of health care professionals are influenced by their personal characteristics, such as social demographics, perceptions, and other social and cultural factors. Psychological theories have been used in studies focusing on human behavior where the results could predict human information security practices [31]. Individual health care professionals' security-related behavior can also be linked to their unique activities for constructing unique profiles in access control-related logs, such as browser histories, access logs, and network and operating system logs, in the context of big data [32]. Attack and defense simulations can also reveal health care professionals' security behavioral risk levels. In using health care information systems, employees' practices, induced by their characteristics, can have a positive or negative impact on information security [33]. Password management, physical security measures, users' responses to phishing attacks, and users' handling of resources entrusted to them by virtue of their user credentials are all examples of employee security practices [4]. The psychosociocultural (PSC) framework discussed in this paper focuses on perception and social, cultural, and sociodemographic variables. Therefore, the PSC framework depends on human behavioral theories, and individual- and work-related demographics [13] for assessing behavioral gaps in health care professionals' security practices. Information security issues in health care can no longer be mitigated by technological countermeasures alone because the problem stems

from health care professionals' security practices, so enhancing "human firewalls" is necessary to mitigate the problem [11]. A human firewall involves strengthening the conscious security behaviors of health care workers in order to avoid security malpractices, such as falling victim to social engineering tricks. Strengthening the conscious security behaviors would augment the technological countermeasures, which would then enhance the overall security situation in health care. Frameworks for modeling and analyzing users' security practices require comprehensive behavioral theories to study health care professionals' practices for related security metrics and to identify potential mitigation strategies. Significant information security issues relating to psychological, sociocultural, and demographic factors could undermine information security policies and regulations, which could lead to information security violations [15].

PSC characteristics in this study refer to personal aspects, such as perceptions, attitudes, norms, and beliefs, as well as social and cultural factors that can influence the security practice of health care professionals [23]. Sociodemographic characteristics in this study include age, gender, education, workload level, work emergency situation, and security experience, while psychological, social, and cultural characteristics as a whole refer to health professionals' security behaviors that are influenced by their psychological, social, and cultural factors, such as perceptions, workplace peer pressure, attitudes, norms, social bonding, and beliefs [23].

In a security practice analysis, the identified theories are usually related with various security practices. Peasons et al identified internet use, email use, social media use, password management, incident reporting, information handling, and mobile computing as comprehensive security practices in their survey work [34,35]. These security practices encompass a comprehensive list of the security practices that are most prone to security violations and compliance, and represent all sections of an information security policy that are essential to safeguard the confidentiality, integrity, and availability of information [4,35]. These security practices were compiled from the Human Aspect of Information Security Questionnaire (HAIS-Q) and from security standards and policies [35]. Other security practices were identified in previous studies [8,36], but the security practices in these studies were less comprehensive as compared to the HAIS-Q. Prior to usage, the HAIS-Q must always be updated to reflect current information security standards and policies [37].

Security Practices

As outlined in the HAIS-Q, health care professionals' security practices include the security measures being adopted in the information security usage activities in response to security policies to safeguard the confidentiality, integrity, and availability of health care information systems. The requirements for such practices are usually expressed in regulations, directives, legislations, and security policies and specified in standards, best practices, and codes of conduct. Health care professionals' security practices include security measures being adopted in the usage of the internet, email, and social media; password management; incident reporting; information handling; and mobile computing [24], as required by information security

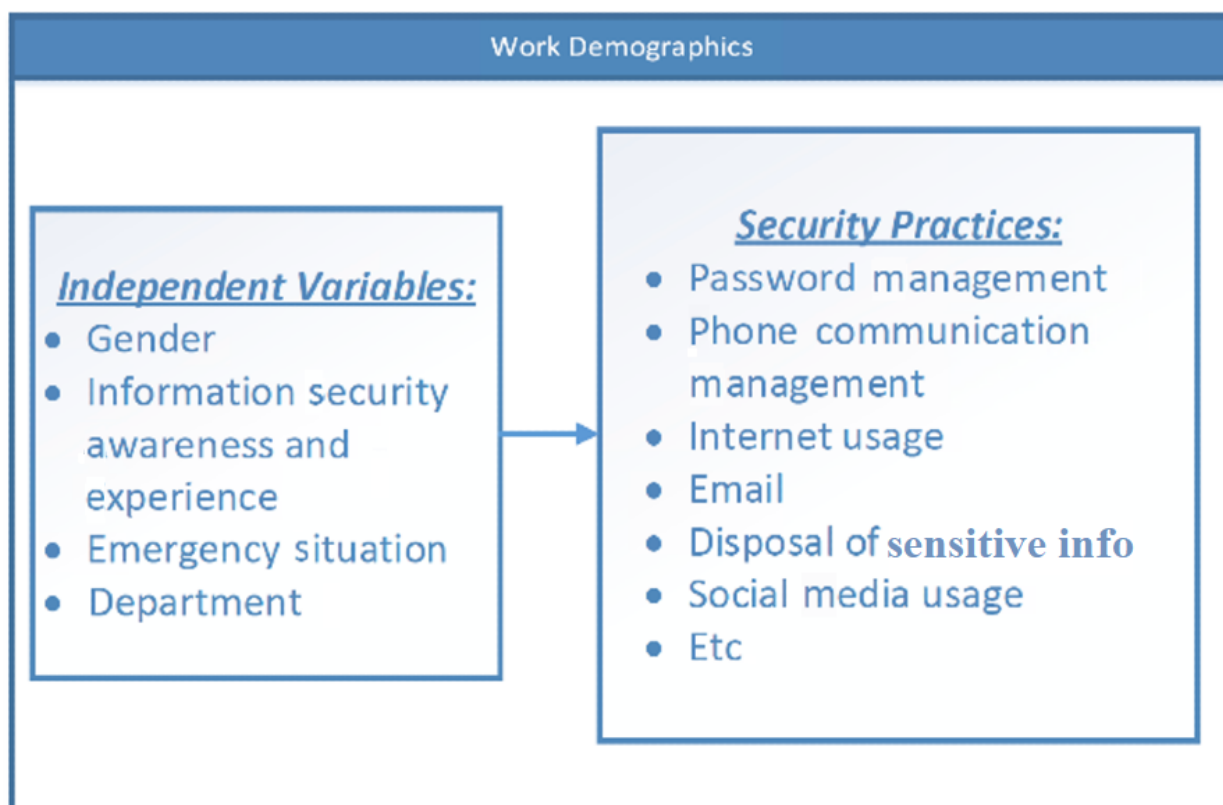
policies and standards. For instance, in password management, how do users respond to periodic password changes as required by some security policies? When modeling human behavior with these theories, independent variables (eg, professionals' associated characteristics or constructs shown in Table 1 [4,8,14-16,18,21,34,35,38-40] and Figure 1) are often explored with mediating variables (Figure 1), such as the professionals'

security practices [25,26]. Therefore, comprehensive security practices are needed to address those aspects most prone to security violations, to ensure compliance, and to represent all sections of an information security policy that are essential for safeguarding the confidentiality, integrity, and availability of health care resources [27].

Table 1. Psychological, sociocultural, and demographic constructs.

| Construct | Definition, hypothesis, and the effect on security practice |
|-------------------------------|--|
| Social demographics | Social demographics refer to professionals' demographics and work-related factors that influence their security practices [18]. Gender, workload, work emergency, role, department, and awareness or experience in information security all influence professionals' security practices. During health care emergencies or some health care scenarios, health care professionals behave contrary to established security policies if the security measures obstruct health care or threaten patient privacy. Such behaviors adversely impact security [8]. Individual differences also influence security practices [38]. |
| Psychological characteristics | Psychological characteristics in this study refer to an individual's traits, perceptions, beliefs, thought processes, etc. These characteristics are influenced by various factors, including environmental factors [21]. Perceived threat severity, perceived susceptibility, perceived barriers, perceived self-efficacy, cues to action, attitude or personality, and emotions are some of the psychological characteristics that influence health care professionals' security practices. If health care professionals increase their awareness of the adverse impact on security, they tend to behave more consciously [14,38]. |
| Social factors | Social factors refer to the influence of peers and other professional groups. Social bonding, peer pressure, and trust level impact health care professionals' security practices [4,21]. Due to trust and social bonding among health care professionals, conscious care behaviors tend to be adversely affected among them [15,16]. |
| Cultural characteristics | Environmental norms, cultural beliefs, and assumptions impact security practices [4,21]. This study mainly focuses on organizational culture and excludes the potential effect of national cultures. However individuals' cultural backgrounds also impact security-related behavior [34,35,39,40]. |

Figure 1. Relating independent variables with security practices.



Related Frameworks

In contributing to security conscious care behavior among health care workers, Humaidi et al developed a conceptual framework

for determining the statistical significance of perceptions [31]. The study focused on security awareness and security technology related to health care professionals' security conscious behaviors. Protection motivation theory (PMT) and

health belief model attributes were used as independent variables to determine their impact on security awareness and security technology mediating variables.

Similarly, Cannoy et al employed the technology acceptance model (TAM), the theory of reasoned action (TRA), information assurance and security ethical behavior, organizational culture, and health information management [7] to develop a related framework. In the same context, Fernandez-Aleman et al advocated for more security awareness training to enhance good security practices and called for preventive and corrective actions to curtail incidents attributed to health care professionals [41]. The researchers studied the PSC context and some social demographic characteristics (age, gender, and experience). The security practices included password management, unauthorized access, disposal of sensitive information, and incidence reporting. The findings of the research provided some knowledge on the security gap between health care professionals' required and actual information security practices.

Furthermore, the PMT and theory of planned behavior (TPB) [14] were adopted in a study to determine whether information security awareness, information security policy, and experience ultimately impact employee security practices. TPB relies on attitudes, subjective norms, and perceived behaviors to predict human behavior [42,43]. The PMT deals with the ability to protect oneself from threats based on the perceived severity of a threat, perceived probability of occurrence or vulnerability, impact of the recommended preventive practices, and perceived self-efficacy [14]. Additionally, Hassan et al proposed a conceptual model for determining the drivers of information security culture in the health care context [44]. Secondary data were explored for the framework, and the researchers proposed that information security culture is influenced by behavioral change management, information security awareness, security requirements, and organizational systems and knowledge.

Relatedly, Box et al reviewed the literature and proposed a model for information security compliant security practices within health care environments [16]. The researchers aimed to provide an overview of factors that were influencing or discouraging information security compliance. The constructs used in the model included compliance-promoting and misuse-deterrence factors, body of knowledge, attitudes, skills, behavioral interventions, and security compliant behavior.

In an effort to improve health care professionals' conscious care behavior, van Deursen et al aimed to understand the sociotechnical risks of information security in the health care sector [45]. The study excluded the technical aspects of information security risks but focused on information security risks related to human and organizational factors. The researchers explored security incidents recorded in a central database by the Freedom of Information officers of the Scottish Health Boards and English Care Trusts.

Various theories are used to model and assess the security practices of users. Cheng et al identified such theories, including the TRA/TPB, general deterrence theory, PMT, and TAM, as the most widely used theories for studying human security practices in the PSC context [33]. The systematic review

provided knowledge in common theories, but guidelines were not provided on the selection and application of these theories.

Similarly, Yeng et al surveyed for related theories, security practices, and evaluation methods [4]. They found various theories that can be employed in modeling and analyzing health care security practices, as shown in [Multimedia Appendix 1](#); however, the approach was less systematic and lacked a framework.

Health care security practices are not only impacted by social demographic traits (eg, age, gender, and experience) [27,46,47] or psychological traits, but also potentially influenced by other critical factors, such as emergency situations and workload, as shown in [Figure 1](#).

In view of the shortfall of the above framework to allow for the efficient study of health care professionals' security practices, we proposed the PSC framework to create a holistic set of health care professionals' characteristics for analyzing a wide range of security practices.

Problem Specification, Scope, and Contribution of the Study

Information security issues attributed to the human element have been recognized to be as important as technological security measures. Therefore, various frameworks have been developed in the PSC context, but none is comprehensive within this study scope. Some of the frameworks were developed to assess only perception variables [4,26,33,36,37,40]. Other frameworks adopted only social constructs [4,7,35,42,43] or cultural factors [33,48,49]. However, in a scenario where a study must be conducted with the aim of comprehensively understanding and addressing the information security challenges often faced by health care professionals, it is important to know which of the existing frameworks will be adequate. The reviewed frameworks [8,14-16,31,38,41,44,45,49-66] were not fully comprehensive. Meanwhile, security issues are affected by all these aspects and not just psychological, social, cultural, or sociodemographic aspects alone [38]. Therefore, a framework that can include all these aspects ([Multimedia Appendix 1](#)) will be a comprehensive one. Furthermore, it is necessary to systematically structure the knowledge in a way that explicitly shows the connection between concepts in the study domain by using appropriate methods such as a domain ontology.

This study proposes a holistic framework that consists of psychological, sociodemographic, and sociocultural variables, which can be used to analyze a comprehensive set of health care professionals' security practices, as shown in [Table 1](#).

The framework builds on studies collected in a literature review, as shown in [Multimedia Appendix 2](#). In order to comprehensively and explicitly represent the domain of interest, we also produced a domain ontology for developing the PSC framework. The purpose of the ontology is to enable the creation of a common understanding among people or software agents within a domain to share, reuse, and analyze domain knowledge [67,68]. The security issues in health care organizations not only are attributed to health care workers' behaviors, but also stem from security awareness and organizational factors, such

as IT competence of business managers, environment uncertainty, industry type, organizational preparedness, organizational culture, top management support, and organizational size. Various studies identified that organizational factors, including organizational size and industry type, have strong influences on IT [69-71] and implementation of information security management [72]. Notwithstanding, the scope of this study does not cover all organizational factors, but considers organizational factors and top management, with much focus on security issues directly involving health care workers, such as health care professionals who provide therapeutic measures (doctors, nurses, pharmacies, laboratory personnel, radiology officers, etc), IT personnel, health administrators, and finance personnel. The next section outlines the methods used in this study.

Methods

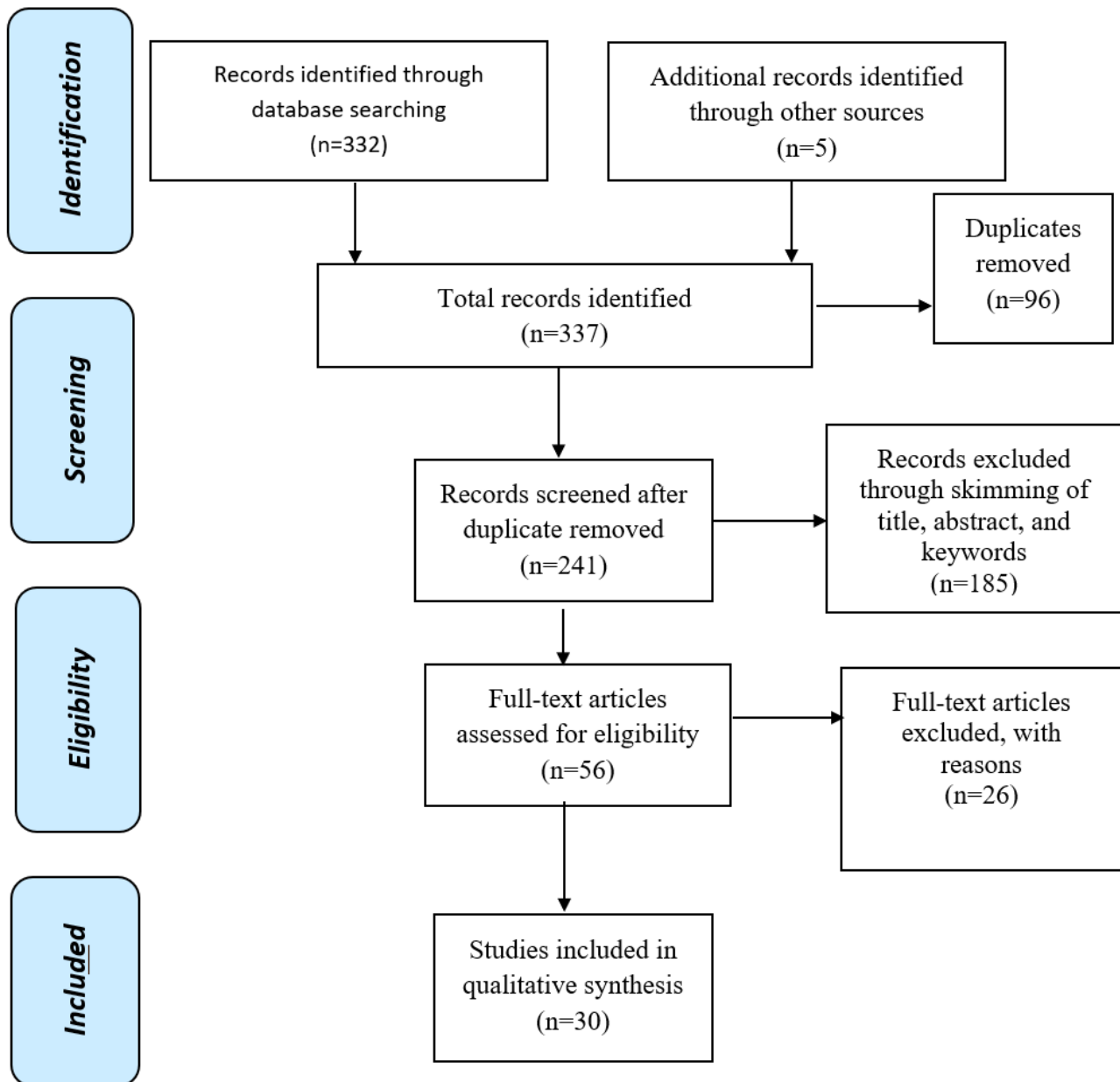
General Approach

We conducted a literature review of the state-of-the-art theories and security practices in health care in order to develop a holistic framework. According to previous reports [73-76], there are various types of systematic studies. These include systematic mapping studies and systematic literature reviews. Systematic mapping studies perform reviews of topics in a broader sense by categorizing basic research articles into specific areas of interest. Systematic mapping studies have general research questions aimed at determining research trends or state-of-the-art studies. Systematic literature reviews aim to aggregate evidence and therefore have a relatively specific research goal. To this end, a systematic mapping study was adopted in this work [73,74]. Based on a review, we built and used an ontology to develop the PSC framework, which covers most of the dimensions of health care professionals' security-related traits.

This framework allows for holistically analyzing health care security practices.

The literature search was conducted between June 2019 and December 2019 through Google Scholar, Science Direct, Elsevier, IEEE Explore, ACM Digital, PubMed, and Scopus. Different keywords, such as "healthcare," "health," "staff," "employee," "professional," "information security," "behavior," and "practice" were used. To ensure a good-quality search strategy, the keywords were combined using the Boolean functions "AND," "OR," and "NOT." Peer-reviewed journals and articles were considered. The inclusion and exclusion criteria were developed based on the study objective and through discussions among the authors. Initially, 337 articles were selected by skimming through the titles and keywords for articles that aligned with the inclusion and exclusion criteria. Screening was further applied by quickly reading the abstracts and keywords. Duplicates were then filtered out, and articles that appeared relevant, based on the inclusion and exclusion criteria, were read in their entirety and evaluated. Twenty-six articles were further removed from the study in the full reading and evaluation stage based on various reasons, including limited scope and articles not meeting the inclusion and exclusion criteria. For instance, a study [77] looked into security issues in health care using a machine learning approach, but this was out of the scope of this study. Furthermore, another study [78] looked into an assessment model for software quality issues in health care, but security was not the main focus. Based on these and other similar reasons, the number of articles included in this study reduced greatly. Other relevant articles were also retrieved through the reference lists found in the literature. Figure 2 presents a Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) flow diagram that clarifies article selection and screening [79].

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart.



Inclusion and Exclusion Criteria

Articles included in the review were required to be about security practices in the health care context and to pertain to health care professionals' information security behaviors in relation to their work. Other articles, such as those that were not related to the health care context and did not focus on human behavior in health care, were excluded.

Data Collection and Categorization

Data collection and categorization were established from the study objective through completion of the literature review and based on discussions of the authors. In order to assess, analyze, and evaluate the study, these categories were exclusively defined as follows:

1. Theory used: This category included only theories (psychological, social, or cultural theories) used in the study to relate human characteristics to security practices.

2. Security practice: This category included the security measures (eg, password management, incident reporting, and internet usage) used in the study.
3. Study type: This category specified the type of study, whether theoretical or empirical. In this study, "empirical" refers to practical studies conducted in the health care context and "theoretical" refers to reviews and proposed frameworks for related studies.
4. Study context: This category specified what area (eg, psychological, social, cultural, or demographic context) the study covered.

[Multimedia Appendix 2](#) presents the categorization of the included literature.

Literature Evaluation and Analysis

The selected articles were assessed, analyzed, and evaluated based on the above defined categories. We performed an analysis on each of the categories (theory used, security practice,

study type, and study construct) to evaluate the state-of-the-art approaches. The percentages of the attributes for the categories were calculated based on the total number of counts (n) of each attribute type. Some studies used multiple categories; therefore, the number of counts for these categories exceeded the total number of articles in the study.

Results

Literature Review Findings

This section presents the findings of the literature review, the ontology, and the proposed theoretical framework.

The searches in the aforementioned online databases resulted in a total of 337 records being initially identified by following

the guidelines of the inclusion and exclusion criteria in the reading of titles, abstracts, and keywords. We further screened and selected articles by reading the objective, methods, and conclusion sections of each study, and this led to a further exclusion of 185 articles that did not meet the defined inclusion criteria. A total of 96 duplicates were also removed, and the remaining 56 articles were fully read and appraised. After the full-text reading, a total of 30 articles were included and analyzed in the study (Figure 2).

Table 2 presents the theories identified in the literature review [4,7,11,14,49,53,59,62,65]. The theories that were most often used in analyzing the security practices of health care professionals included the health belief model (n=6), TPB (n=5), general deterrence theory (n=4), PMT (n=4), and technology acceptance theory (n=2), as shown in Table 2.

Table 2. Psychological, social, and cultural theories.

| Theory | Count, n |
|---|----------|
| Health belief model [49] | 6 |
| Theory of planned behavior [14] | 5 |
| General deterrence theory [53] | 4 |
| Protection motivation theory [14] | 4 |
| Technology acceptance theory [4] | 2 |
| Technology threat avoidance theory [59] | 1 |
| Social bond theory [11] | 1 |
| Situational crime prevention [53] | 1 |
| Institutional theory [62] | 1 |
| Grounded theory [65] | 1 |
| Social control [7] | 1 |
| The big five theory [7] | 1 |

The security practices that were often related with the individual characteristics of the health care professionals at their workplaces included password management (n=6), unauthorized disclosure (n=3), security policy and procedures (n=3), and

email use with sensitive data (n=2), as shown in Table 3 [4,41,45,50,51,60].

The categories of theories frequently identified included psychology (n=7), demographics (n=6), social (n=3), and cultural (n=3), as shown in Table 4.

Table 3. Security practices.

| Security practice | Count, n |
|------------------------------------|----------|
| Password management [41,45,51] | 6 |
| Security policy and procedure [60] | 3 |
| Unauthorized disclosure [60] | 3 |
| Email use with sensitive data [4] | 2 |
| Logging off session [4,50] | 2 |
| Emergency access [4] | 2 |

Table 4. Categories of the studies identified.

| Category | Count, n |
|--------------|----------|
| Psychology | 7 |
| Demographics | 6 |
| Social | 3 |
| Cultural | 3 |
| Linguistics | 1 |

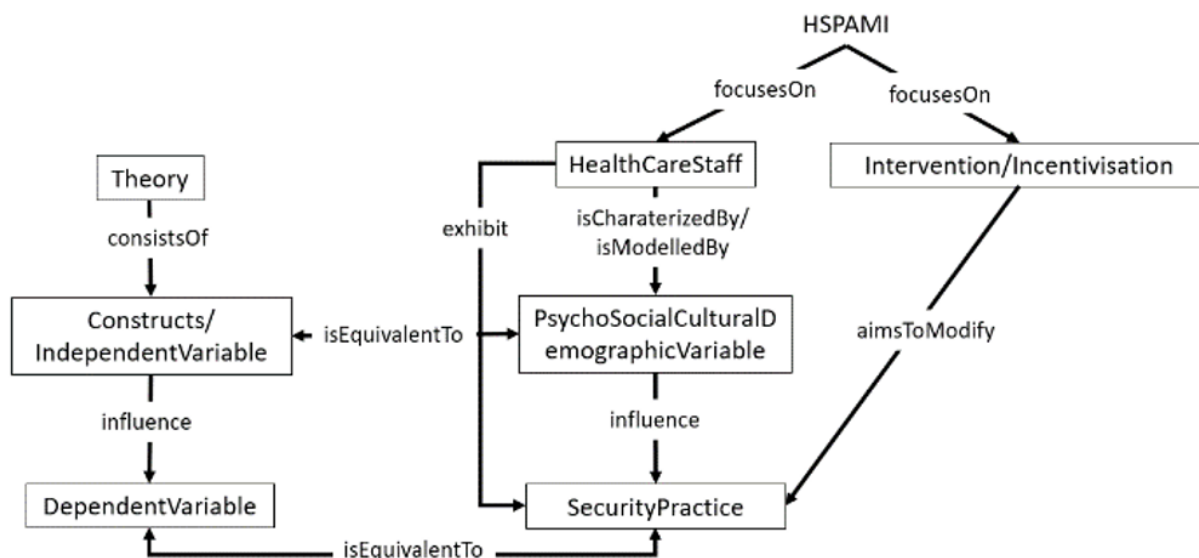
A higher proportion of empirical studies (n=15) was identified, compared with theoretical studies (n=9).

Proposed Ontology

Ontologies are formal specifications of key concepts within a domain and the relationships among them. Ontologies are purposeful artefacts that make domain assumptions explicit, enable the construction of a common understanding among stakeholders, enable the reuse of expert knowledge, etc [51].

The proposed ontology contained a total of eight distinct concepts and nine relationships, which enabled us to capture the conceptual relationship between a total of 76 unique instances extracted from the literature. Figure 3 presents the ontology capturing key concepts of the HSPAMI project and the supporting empirical evidence that corresponds to the PSC framework. The following subsections describe the steps followed for the construction of the ontology based on the guidelines presented in a previous report [67].

Figure 3. Structure of the ontology representing concepts as classes and specifying the relationship among the classes. The relationships among concepts are represented by the arrows between concepts in the rectangles. HSPAMI: Healthcare Security Practice Analysis, Modeling, and Incentivization.



Development of the Ontology

The main objective of the proposed ontology was to map the HSPAMI main study areas to empirically supported research results in order to develop a literature-based comprehensive holistic framework that can be utilized in the project and by researchers or practitioners interested in the domain of information security within the health care context [4].

Determine the Domain and Scope of the Ontology

The proposed ontology aimed to (1) structure the main focus areas of the HSPAMI project, (2) create a connection between these study areas and existing empirical research results, and (3) develop a comprehensive PSC framework that efficiently communicates domain knowledge to various stakeholders. Thus, the domain is defined as health care professionals’ security practices, and the scope is restricted to research results

investigating the relationship between psychological and sociocultural theories and variables with respect to security behaviors.

Use of Existing Ontologies

Literature searches were conducted for existing comprehensive domain ontologies on Google Scholar, ScienceDirect, and Scopus, with the following keywords: “ontology,” “healthcare,” “security behavior,” and “practice.” These keywords were also combined with the Boolean functions of “AND,” “OR,” and “NOT.” No comprehensive ontology was identified. Ontologies that explicitly model and structure the domain have been proposed for various purposes in the health care domain, such as interoperability [80] and regulating access control for internet of things–based health care [40,81]. The ontology proposed in this paper uses the HSPAMI study areas as an organizing

principle for the existing empirically supported research results [40,81].

List of the Relevant Terms of the Domain

The fundamental concepts were identified in a previous report [4] with respect to the main study areas of the HSPAMI project. These are health care professionals’ psychosocial and cultural demographic variables, security practices, and incentivization of security practices. The concepts were aligned with the classes commonly encountered in empirical studies investigating the relationship between theoretical constructs and behaviors of interest or outcome variables (eg, security practices).

Define the Classes and the Class Hierarchy

In order to represent the relationship between concepts of the domain and empirical research results, the classes were conceptually connected to each other. The combination approach

was followed in defining the classes and hierarchy, which combined top-down and bottom-up approaches. More salient concepts (HSPAMI concepts and study components) were defined first, and then, based on the identified empirical results, more specific concepts were included. To deal with different terminologies applied to similar concepts (synonyms), the equivalence of classes was represented by the “isEquivalentTo” relationship between concepts, which was inherited by the instances added to the classes. Thus, theories that consisted of constructs could be included in the ontology by defining and connecting an instance to the accompanying theory. Variables that were not specifically part of any theory (eg, demographic variables) could be included by restricting the domain attribute to the class of constructs. Table 5 shows the existing classes defined within the ontology, with example instances. Based on the literature review, a total of eight classes were defined as the most general concepts, as shown in Figure 3.

Table 5. Main concepts defined as classes.

| Classes | Instances |
|---|---|
| HSPAMI ^a | — ^b |
| HealthCareStaff | Doctors, nurses, etc |
| Intervention/Incentivization | Motivation, deterrence, etc |
| PsychoSocialCulturalDemographicVariable | Gender, age, etc |
| SecurityPractice | PasswordManagement, EmailUse, etc |
| Theory | Theory of planned behavior, protection motivation theory, etc |
| Construct/IndependentVariable | Attitude, SubjectiveNorm, etc |
| DependentVariable | ActualBehavior, SecurityAwareness, etc |

^aHSPAMI: Healthcare Security Practice Analysis Modeling and Incentivization.

^bNo instance.

Define Properties of Classes

The main objective of this step was to describe the relationship of a class to other individuals. The properties were defined at

the most general class; thus, all members of that class inherited the given property. Table 6 shows the relationships and the connected classes in the proposed ontology. A total of nine properties link various concepts in the ontology.

Table 6. Relation of classes.

| Relation of classes | Classes connected |
|-------------------------------|---|
| consistsOf | Theory - Construct |
| influence | IndependentVariable - DependentVariable |
| isEquivalentTo | Construct - PsychoSocialCulturalDemographicVariable |
| exhibit | HealthCareStaff - SecurityPractice, DependentVariable |
| isCharacterizedBy/isModeledBy | HealthCareStaff - Construct |
| aimsToModify | Intervention/Incentivization - SecurityPractice |
| focusesOn | HSPAMI ^a - Intervention, HealthCareStaff |
| isATypeOf | Gender - Construct |
| hasAttribute | SelfEfficacy - Psychological; Gender - Demographic |

^aHSPAMI: Healthcare Security Practice Analysis Modeling and Incentivization.

Define the Data-Type Properties

This step was excluded in the development of the ontology at this stage. Since ontologies can be developed at various levels of granularity, these steps may be iteratively completed at a future stage when the requirements (eg, development of software) are defined more specifically. For the purpose of creating a comprehensive framework of health care staff characteristics and security practices, this step was unnecessary.

Create Instances

The research papers meeting the inclusion criteria were subsequently analyzed in detail to extract instances for the previously enumerated classes. The list of papers reviewed for constructing the ontology are presented in [Multimedia Appendix 3](#).

For the purpose of demonstration, [Figure 4](#) and [Figure 5](#) present how instances can be included in the existing ontology. Additional properties (eg, equivalence of classes) can be represented, which is especially important to avoid ambiguity and for clarifying the semantic meaning of different concepts when they are related (eg, self-efficacy is equivalent to perceived behavioral control). Each theory discussed in a previous report [82] was represented as an instance of the theory class, and the object property “isATypeOf” was proposed to capture the relationship. The TPB consisted of the following three constructs: “AttitudeTowardBehavior,” “SubjectiveNorm,” and “PerceivedBehavioralControl,” which can be considered equivalent to beliefs related to self-efficacy.

Figure 4. Instances and additional properties defined from the review paper [38]. GDT: general deterrence theory; PMT: protection motivation theory; TAM: technology acceptance model; TPB: theory of planned behavior; TRA: theory of reasoned action.

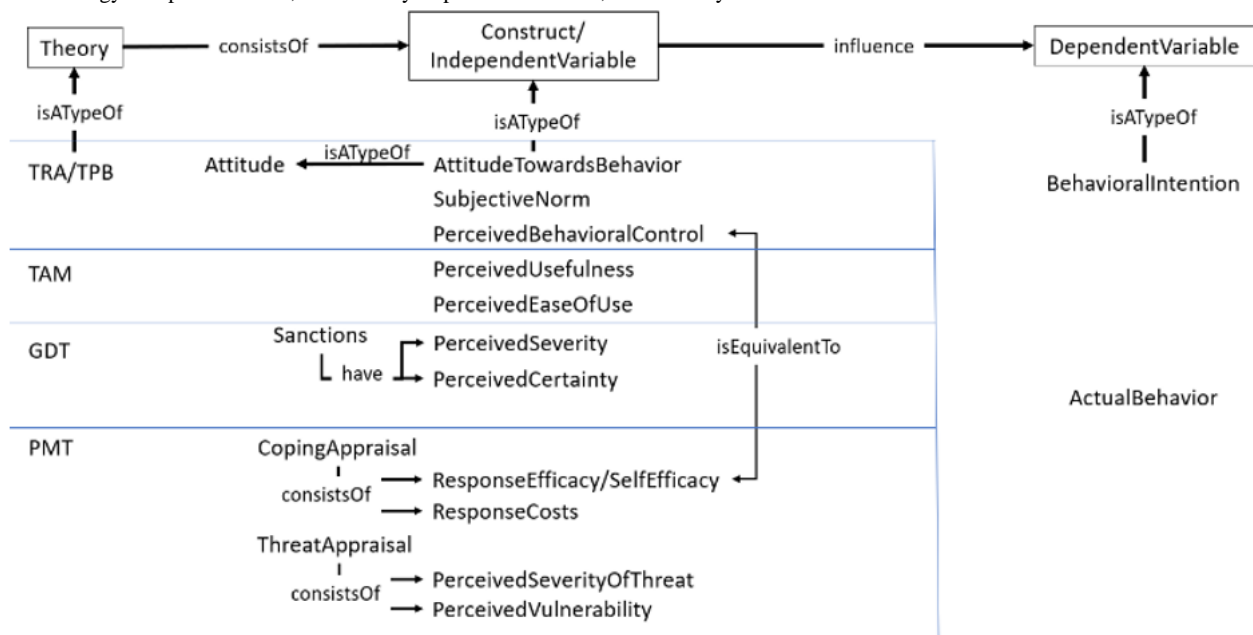
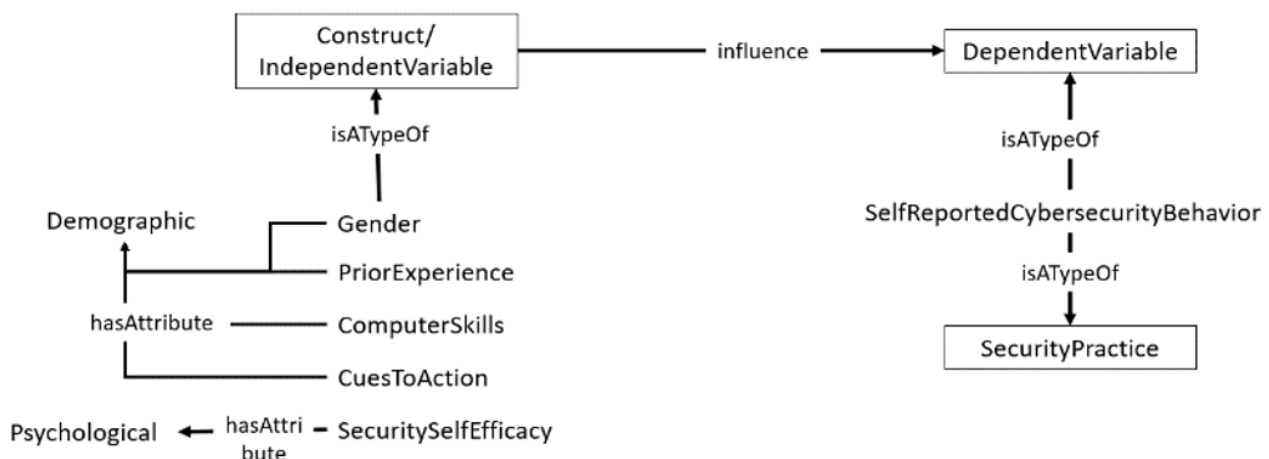


Figure 5. Expansion of the ontology based on results from a previous report [38].



Ontology and the PSC Framework

The framework shown in [Figure 6](#) consists of independent variables, mediating variables, and the dependent or target

variable. The independent variables have various constructs, including psychological traits, social factors, cultural influences, and sociodemographic characteristics. Attributes of these constructs were associated with comprehensive security

practices. The security practices served as mediating variables. The target or dependent variable, known as health care professionals' security metrics, was obtained after relating the independent and mediating variables. The framework components are as follows:

1. Independent variables: This aspect of the PSC framework consists of the characteristics of the health care staff that can impact health care professionals' security practices. With reference to Figure 4 and Figure 6, these characteristics are segregated into psychological or perception variables, sociodemographics, and social and cultural attributes. The psychological traits include perception variables or constructs, such as perceived

- 2. severity, perceived susceptibility, perceived cues to action, perceived barriers, and perceived self-efficacy, personality, and emotions.
- 2. Social bonding: Social bonding is related to social behaviors that can influence health care professionals' information security behaviors. Such constructs include social bonding, peer pressure, and trust level, as shown in Figure 6.
- 3. Cultural factors: Culture-related traits that can impact information security include environmental norms, beliefs, and assumptions.
- 4. Social demographics: Social demographics, such as gender, workload, information security experience, emergency, role, and experience, are hypothesized to have an impact on information security relating to health care staff.

Figure 6. Proposed psychosociocultural framework.

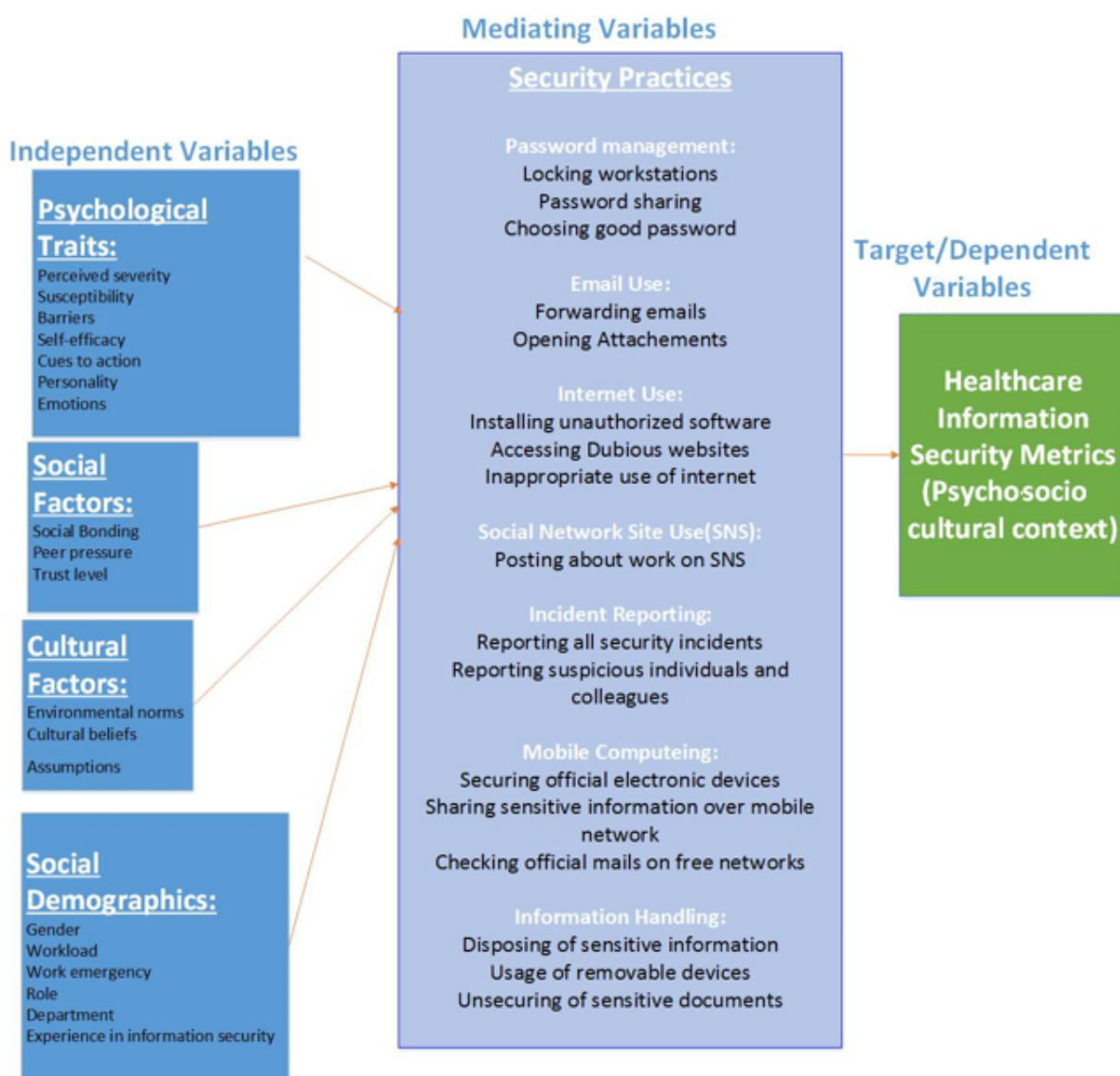


Figure 4 presents the expansion of the ontology with empirical results that have particular theories associated with them. Psychological, cultural, and demographic variables were grouped by defining additional attributes to facilitate knowledge sharing.

The PSC framework also has mediating variables that are basically the security practices of the health care staff. The health care security practices are the required security-related behaviors defined in the policies, standards, regulations, and codes of conduct for health care personnel. Health care staff are therefore required to abide by such security measures to enhance

the confidentiality, integrity, and availability of health care data. The security practices in the PSC framework were adopted from the HAIS-Q. The HAIS-Q is a framework consisting of a comprehensive information security practice. In a typical health care environment, health care staff members go through their daily security practices within the scope of the HAIS-Q, and these security practices are impacted by independent variables. Security practices include social network usage, password management, incident reporting, mobile computing, and internet use, as shown in [Figure 6](#).

Finally, the target or the dependent variable is the measured security practice of health care staff. Such a security metric can therefore be used for management decision-making, such as implementing intervention measures aimed to improve conscious care security practices.

Discussion

Principal Findings

Information security management for mitigating data breaches involves identifying the threats to information security and devising efficient countermeasures [28]. Information security management includes adding tools and serving employees with checklists of information security user policies for work roles, as well as requiring employees to abide by those policies. However, the security of health care data also requires systematic analysis of the health care professionals' security practices for building a "human firewall," with the objective of enhancing a conscious care and security resilience culture. Thus, identification of various sources of human threats in the social, cultural, and psychological contexts is vital [12,34,35,39].

To this end, we identified constructs capturing psychological, sociocultural, and demographic variables (termed in this study as "psychosociocultural context") to develop the PSC framework to understand health care professionals' security practices. The main contribution of this paper is the development of the PSC framework implemented as a domain ontology. Specifically, the framework includes concepts and important variables that have been empirically proven to influence the behavior (ie, security-related practices) of health care professionals when dealing with sensitive information in a health care work setting.

Based on the overview of existing literature [8,14-16,31,38,41,44,45,49-66], we concluded that existing frameworks lack a comprehensive and holistic perspective. Furthermore, not all frameworks provide strong empirical support for the inclusion of variables from the perspective of both security-related-behaviors and professionals' characteristics [14,45,49,52,55,57-59]. Therefore, this paper represents a step toward creating a comprehensive and practically useful framework that can aid information security practitioners in fulfilling their work requirements by incorporating relevant concepts and research results that serve as a foundation of the framework.

The utility of the proposed framework will be tested in the HSPAMI project by scoping the forthcoming investigations on factors that must be considered in monitoring and modifying health care professionals' security-related behaviors. While

specific empirical research papers are necessarily limited with respect to their scope on the security practices and the theories utilized, such papers provide the crucial building blocks of the overarching framework. The first major advantage of the present framework is that it encompasses accumulated knowledge by utilizing the evidence from previous investigations (each focusing on narrowly defined behaviors [8,33,35,38,45,48,82-84], eg, responding to spam and sharing information on social media); thus, the framework provides a more comprehensive perspective on the various forms of security-related behaviors that should be investigated. This aspect of the present framework is mainly supported by the inclusion of the concepts found in the HAIS-Q instrument, which is a validated and widely utilized questionnaire for measuring information security-related beliefs, knowledge, and attitudes [34,35,39].

Based on the literature survey, we also developed an ontology to include significant concepts for the development of the PSC framework. Within the PSC context of health care professionals' security practices, various studies exist [14,31,41]. The second major contribution therefore involves the selection of psychological, social, and demographic variables (ie, constructs and theories) from existing literature [8,33,35,38,45,48,82-84] and the representation of the framework in the form of a domain ontology. By specifying the framework as an ontology, we can efficiently structure, organize, and reuse the vast amount of existing knowledge. Furthermore, the ontology also enables an efficient way to share information with other stakeholders within and outside the HSPAMI project without ambiguities, thus helping to build a common understanding. This aspect is exemplified by object relations that link synonyms or different terminologies used for the same construct to build a common language shared by all stakeholders involved in project-related activities. Finally, the ontology may as well serve as a blueprint for applications developed within the project, such as relational databases containing relevant variables and specifying the connections between them.

Evaluation of the ontology refers to judgments about the technical features of the ontology and assessment of its usability and utility. Generally, evaluation aims at ensuring the correctness and completeness of an ontology [85]. It is an iterative process, which can be conducted at each point of the ontology's life cycle. An evaluation must be done against a frame of reference, which may be a set of competency questions and requirements, and the real world [85], and may take the form of a technical evaluation in the lab or at the location of application (eg, health care context with health care professionals). Evaluation may be performed with several criteria as follows: evaluation of definitions (checking for the absence of well-defined properties in the ontology), structure of the ontology (matching the ontology's structure with the design criteria of the environment, where it is intended to be used), syntax of definitions (ensuring that syntactically correct keywords are present), content of definitions (identifying what concepts are covered and what concepts are not included or included incorrectly), consistency (avoiding contradictions), completeness (extent of covered concepts in the domain of interest), and conciseness (checking whether information

contained in the ontology is relevant and accurate) [85]. As the ontology has been developed using existing empirical research results, its validity partially depends on the reliability and validity of the findings in the knowledge base. Furthermore, at this stage of development, only a technical evaluation is possible; thus, its validation in real-world settings is among the key goals of future work. Eventually, the practical benefits of the ontology depend on its recognition and approval among experts who utilize it [86].

With respect to the comprehensiveness of the current PSC framework, it is comparable to similar approaches [7,31] with a stronger focus on the requirement that only empirically supported research results are included. While this may limit the comprehensiveness of the framework, it ensures that only relevant and practically significant theories and concepts are investigated and applied during the activities of the overall project, which can save time and other valuable resources during the process. The real-world evaluation of the framework in terms of its usefulness for sharing and analyzing knowledge, creating a common understanding, and representing concrete aspects of the envisaged application domain will be studied within the scope of the project through case studies, field experiments, or other research methods.

To complement the efforts of health care professionals in maintaining the confidentiality, integrity, and availability of health care data, a systematic approach to identify the detailed and subtle health care professionals' characteristics that impact information security practices must be applied. All these constructs are vital when measuring the conscious care behavior of health care professionals. For example, if we assume that psychological constructs are not measured in a typical empirical study of security conscious care behaviors, there will be a gap since the perception of the health care security practice will not be captured [12]. Thus, if security solutions are professed based on such a study, the solutions will lack measures to deal with the perception aspect.

Therefore, through the PSC framework developed in this paper, we identified various constructs within the project domain. The holistic approach is much needed because it strives to capture the entire problem area in the scope of the project. Focusing on just one or two aspects of staff-related traits that impact security in the health care industry might not be sufficiently effective [12]. For instance, some of the frameworks focused only on social factors, with the exclusion of other factors, such as the perception. Without determining how health care staff perceived the severity of the impact of their information security malpractices in a related study, health care professionals may not be treated with appropriate incentivization methods for improving such malpractices. Lack of perception variables implies that health care staff would not be able to perceive the gravity of their security-related malpractices, which means there may still be data breaches resulting from untreated psychological traits. Conversely, if a study is conducted with only psychological constructs, data breaches may still occur as a result of untreated social-related constructs, such as social

bonding and peer pressure. An approach, such as the PSC framework, therefore appears necessary for an efficient study.

Conclusion and Future Work

The mutual trust between health care professionals and their patients is under threat owing to frequent and large data breaches in health care. Furthermore, the richness of health care data is attracting cyber criminals. Since scaling universal technological security measures is challenging, cyber criminals tend to exploit health care staff for easy entry.

To curtail this ascendance in data breaches, a comprehensive set of health care professionals' characteristics and security practices, which can impact information security, was identified. An ontology was developed from the identified literature generated by a literature review. Then, a holistic PSC framework was developed. The framework can be implemented with a mixed method approach encompassing both qualitative and quantitative studies [45,87].

Owing to the systematic approach used to develop the PSC framework, it is possible to identify reliable security metrics while considering all the subtle characteristics of health care professionals and their related security practices. Such metrics can then be used to develop incentivization or motivational measures aimed toward building stronger "human firewalls" to curtail data breaches in health care. Beyond the conventional qualitative evaluation methods of interviews and questionnaires or surveys, other approaches, including team-based learning [87] and the Delphi method [45], should be explored in the future to enrich empirical studies using comprehensive frameworks such as our PSC framework. Additionally, organizational factors should be considered in the future, since they were not entirely covered in this study.

Furthermore, clarifying the meaning and interconnectedness of various terms imported from different domains (eg, psychology, information security, sociology, etc) can be beneficial for discovering contradictory or converging pieces of evidence revealed by researchers. While the ontology currently captures only a limited number of concepts from the PSC and demographic contexts of health care professionals, it is flexible and can be extended with new results based on advances in the literature. The level of granularity can, for instance, be increased depending on the requirements of the applications in future work. The emphasis on empirical foundations could also be strengthened by representing associations between variables through specifying additional object properties associated with the classes (eg, correlations, predictive accuracy, etc). The compatibility of this domain ontology with other ontologies (eg, health care staff demographic characteristics in employee databases) needs to be investigated in future work to increase reusability and to achieve more realistic mapping between research results and the opportunities to observe the variables included in the framework. Additional expert knowledge could be useful for enriching the framework, and this can be achieved through iterative workshop sessions with other stakeholders (eg, health care staff, security practitioners, etc).

Conflicts of Interest

None declared.

Multimedia Appendix 1

Analysis of the theories and their application areas in the Healthcare Security Practice Analysis Modeling and Incentivization (HSPAMI) project [[xref ref-type="bibr" rid="10ref4">4</xref>\].](#)

[[DOCX File , 14 KB - humanfactors_v8i2e17604_app1.docx](#)]

Multimedia Appendix 2

Summary of the literature review.

[[DOCX File , 18 KB - humanfactors_v8i2e17604_app2.docx](#)]

Multimedia Appendix 3

Articles used to construct the ontology.

[[DOCX File , 17 KB - humanfactors_v8i2e17604_app3.docx](#)]

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Abbreviations

GDPR: General Data Protection Regulation

HAIS-Q: Human Aspect of Information Security Questionnaire

HSPAMI: Healthcare Security Practice Analysis Modeling and Incentivization

IT: information technology

PMT: protection motivation theory

PSC: psychosociocultural

TAM: technology acceptance model

TPB: theory of planned behavior

TRA: theory of reasoned action

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Viewpoint

Identifying Barriers to and Opportunities for Telehealth Implementation Amidst the COVID-19 Pandemic by Using a Human Factors Approach: A Leap Into the Future of Health Care Delivery?

Tianyi Zhang^{1*}, MSc; Jarrod Mosier^{2,3,4*}, MD, FCCM; Vignesh Subbian^{1,2*}, PhD

¹Department of Systems and Industrial Engineering, College of Engineering, The University of Arizona, Tucson, AZ, United States

²Department of Biomedical Engineering, The University of Arizona, Tucson, AZ, United States

³Department of Medicine, Division of Pulmonary, Allergy, Critical Care and Sleep, University of Arizona College of Medicine, Tucson, AZ, United States

⁴Adult ECMO Service, Banner - University Medical Center Tucson, Tucson, AZ, United States

*all authors contributed equally

Corresponding Author:

Tianyi Zhang, MSc

Department of Systems and Industrial Engineering

College of Engineering

The University of Arizona

1127 E James E Rogers Way

Tucson, AZ, 85721-0020

United States

Phone: 1 6088863936

Email: tianyi@email.arizona.edu

Abstract

The extensive uptake of telehealth has considerably transformed health care delivery since the beginning of the COVID-19 pandemic and has imposed tremendous challenges to its large-scale implementation and adaptation. Given the shift in paradigm from telehealth as an alternative mechanism of care delivery to telehealth as an integral part of the health system, it is imperative to take a systematic approach to identifying barriers to, opportunities for, and the overall impact of telehealth implementation amidst the current pandemic. In this work, we apply a human factors framework, the Systems Engineering Initiative for Patient Safety model, to guide our holistic analysis and discussion of telehealth implementation, encompassing the health care work system, care processes, and outcomes.

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KEYWORDS

telehealth; healthcare system; COVID-19; human factors; implementation; SEIPS

Introduction

COVID-19, caused by the novel coronavirus SARS-CoV-2, has swept across the globe since its emergence in late 2019. The rapid spread of SARS-CoV-2 imposed an excessive burden on health care systems, with nearly 326.7 per 100,000 people in the USA requiring hospitalization through the end of 2020 [1]. The extensive adoption of telehealth approaches, as part of protective measures and to promote the overall safety of patients and health care workers, has manifested in various essential components of care delivery. The surge in the adoption of telehealth, however, imposes significant challenges to the health

care system, as it has disrupted the balance of the health care work system, thus highlighting the importance of exploring the barriers to and impact of the pandemic-driven, large-scale uptake of telehealth technologies.

The health care system is particularly vulnerable to novel and highly infectious agents such as SARS-CoV-2 because of the exponentially increased demand of health care resources [2], including ventilators and personal protective equipment (PPE), and the high risk of infection among care providers through aerosol transmission during clinical care [3], especially by asymptomatic carriers. The most widely adopted strategy among

the general public to lengthen the doubling time of the virus and reduce the basic reproduction number, R_0 , involved social distancing to attenuate the proximity and duration of contact with potentially infected individuals. In clinical settings, telehealth solutions have emerged as an effective tool for health care systems to deliver care to patients while minimizing safety risks to both patients and providers by maintaining social distancing.

The Systems Engineering Initiative for Patient Safety (SEIPS) model [4,5] provides a useful framework for analyzing the widespread adoption of telehealth in response to the COVID-19 crisis. This model allows for a comprehensive and proactive assessment of telehealth implementation in the longer term, beyond the pandemic [6]. Previous studies [7-9] discussing barriers to or the impact of telehealth implementation either overlooked patients' perspectives or focused more on certain components of the health care system. Here, we demonstrate the application of the SEIPS model to guide the assessment of the barriers to and impact of telehealth on health care *systems*, *processes*, and *outcomes* during the ongoing crisis. According to the SEIPS model, the health care work system includes the following components: *person*, *technologies*, *environment*, *tasks*, and *organization*.

- The *person* component considers education, knowledge, motivation, and physical and psychological characteristics, as it relates to both patients and health care providers.
- The *technologies* component involves all devices and information systems that are used to deliver care.
- The *environment* component consists of the workstation design, layout, noise, and any existential environmental factors.
- The *tasks* component discusses the content, participation, and demands of the job.
- Finally, the *organization* component emphasizes teamwork, coordination, collaboration, communication, and organizational culture [4].

The SEIPS model also emphasizes that the analysis of processes and outcomes should be based at both the individual level (ie, patients and health care workers) and the organizational level. For example, telehealth can reduce the burden of *environment* infection due to COVID-19, which is an essential process to health care organizations but not necessarily a direct part of patients' care processes. In this work, we use the SEIPS model to discuss barriers related to and impacts of telehealth implementation amidst the COVID-19 pandemic (Table 1). Given that there are few measures to assess outcomes of telehealth during the pandemic, we will also discuss and propose measures that could be helpful in guiding the assessment as well as future scalability and efficacy studies.

Table 1. Assessment of barriers related to and impact of telehealth implementation during the COVID-19 pandemic by using the Systems Engineering Initiative for Patient Safety (SEIPS) model.

| Domain and components | Impact | Issues |
|---|--|--|
| Telehealth-enabled work system | | |
| Person as patients | <ul style="list-style-type: none"> Increased acceptance of telehealth due to convenience | <ul style="list-style-type: none"> Insufficient and variable levels of digital literacy among the patient population Widening of health care disparities [10-12] |
| Person as providers | <ul style="list-style-type: none"> Increased motivation Alleviation of workforce shortage due to the quarantine | <ul style="list-style-type: none"> Mental or physical challenges due to the imperative and wide adoption of telehealth |
| Technologies and tools | <ul style="list-style-type: none"> Enhanced patient and health care worker safety Conserve PPE^a | <ul style="list-style-type: none"> Telehealth may be disruptive and not user-friendly |
| Environment | <ul style="list-style-type: none"> Highlighted the suboptimal and complex environment for telehealth uptake | <ul style="list-style-type: none"> Insufficient communication infrastructure The environment where patients interact with telehealth technology may be suboptimal |
| Tasks for patients | <ul style="list-style-type: none"> Safer and potentially quicker access to care | <ul style="list-style-type: none"> Systemic, informational, procedural gap that patients need to fill in |
| Tasks for providers | <ul style="list-style-type: none"> Clinical and nonclinical services can be safely continued via telehealth | <ul style="list-style-type: none"> Challenges in adapting to changes in job content and demands |
| Organization | <ul style="list-style-type: none"> Formulation of new teams Maximizing the utilization of existing resources to deal with the pandemic | <ul style="list-style-type: none"> Dynamic changes to teamwork Reallocation of accountability and responsibility Redistribution of labor, equipment, information, and funding resources |
| Telehealth-enabled processes | | |
| Care Processes | <ul style="list-style-type: none"> Wide application of forward-triage, tele-intake, and tele-ICU^b Increase in web-based visits replacing in-person visits and mixed processes (ie, some in-person visits and some televisits) | <ul style="list-style-type: none"> Time management is more challenging (eg, a busy lobby makes it easier to accept the physician being late as opposed to being at home waiting alone in the virtual lobby) Telehealth may not lead to a shorter overall time spent in the care system |
| Other processes | <ul style="list-style-type: none"> Reduced demand of other processes that support care processes (eg, reduced environment disinfection needs due to the fewer in-person visits) | <ul style="list-style-type: none"> Information flow may be more fragmented |
| Telehealth outcomes | | |
| Patients' outcomes | Unclear | <ul style="list-style-type: none"> Lack of measures for patient safety and quality of care evaluation |
| Care providers' and organizational outcomes | Unclear | <ul style="list-style-type: none"> Lack of measures for assessing care providers' mental and physical health affected by the surging use of telehealth during the COVID-19 pandemic Organizational outcome related to the pandemic-driven, large-scale uptake of telehealth needs more attention |

^aPPE: personal protective equipment.

^bICU: intensive care unit.

Discussion

Person

During various stages of the COVID-19 pandemic, many health care providers were quarantined after potential exposure to or confirmed infection with the virus, resulting in a limited workforce and a reduced health care system capacity. Telehealth

can facilitate the rearrangement and reassignment of the workforce and maintain the capacity by allowing quarantined health care providers to continue their work without compromising the health care system's safety. Moreover, care facilities that lack telemedicine programs can outsource part of their services to entities with well-established telemedicine programs to meet these goals [13].

Despite the claimed benefits of efficiency and convenience offered by telehealth, not all health care providers have been satisfied with the telehealth options available, even before the COVID-19 pandemic. Preliminary reports from the early phases of the pandemic [8] suggests that health care providers' unwillingness is one of the barriers to telehealth implementation in practice. However, this position does not fully consider latent factors such as technological and administrative issues that lead to the active failure (ie, care providers' unwillingness). Furthermore, there is significant variability in telehealth education and training among clinicians, leading to varying levels of acceptance and uptake. The surging health care demands during the pandemic has forced health care workers to adopt telehealth predominantly for safety reasons. Further research is needed to better understand how the adoption of telehealth demanded by new care delivery protocols may affect health care providers' physical and mental workload.

Patients, on the other hand, are also profoundly influenced by the imperative uptake of telehealth since the beginning of the pandemic. Recent studies have shown that telehealth approaches such as remote video visits in a variety of care delivery contexts is acceptable to patients [14,15]. For example, some patients perceive primary care video visits as convenient and efficient because they can stay in their home environments while seeing care providers; however, they are still concerned about privacy issues [14]. A 2009 systematic review [16] and a recent study [17] have both identified that factors such as human-technology interaction (ie, user experience and usefulness), environment (ie, the context where patients would use telehealth), and patient demographics (ie, socioeconomic status) could influence their acceptance of telehealth. Although the pandemic may have potentially increased patients' subjective acceptance of telehealth, objective barriers still hinder a higher acceptance among patients. For instance, some patients may not have access to technology that enables telehealth, have poor internet connectivity, or face technical challenges in navigating telehealth systems [14,18]. These barriers are particularly encountered by vulnerable populations that need most medical attention during the COVID-19 pandemic. In general, although the public health crisis may improve the overall uptake, penetration, and implementation of telehealth among all populations, it may also intensify health inequities [10-12].

Technologies and Tools

Prior to the COVID-19 pandemic, telehealth was regarded as an alternative form of care delivery to in-person care. It was considered ancillary because telehealth was not widely possible until the widespread prevalence of smartphones [19,20]. Today, telehealth can be realized through a variety of communication modalities depending on institutional and regulatory guidance, such as phone calls, text messaging, email, patient portal, or licensed third-party software, and most of them can be accomplished via smartphones.

A recent study pointed out that the adoption of telehealth can conserve PPE [21], which was severely limited in supply during the pandemic. The demand for acute care surged and quickly surpassed the system capacity in many US states. Therefore, by performing select services via telemedicine, hospitals and

clinics can conserve PPE and extend the time to peak capacity. Even high-volume emergency departments can preserve PPE and safety by performing medical screening exams remotely for patients with suspected COVID-19 [21].

Despite the benefits of telehealth uptake, we cannot assume it would work well within the current health care system. In fact, the telehealth system is deemed as disruptive and not user-friendly by many clinicians [8]. For instance, in large health systems in urban Southwest Arizona, telehealth tools were made available during the pandemic, yet many were impractical or nonviable solutions. Contrary to the report that claimed clinicians' unwillingness of adopting telehealth [8], clinicians were positive about telehealth and eager for its uptake to continue serving their patients during statewide mandatory stay-at-home orders, but they were also frustrated at the obstacles to its implementation. We believe that a redesign of the telehealth system is urgently required and is fundamental to higher levels of acceptance and satisfaction among users, including both patients and providers.

Environment

Despite the convenience that telehealth can provide, the lack of infrastructure and insufficient technical capability may limit providers' and patients' use and acceptance of telehealth. Although the majority of the United States has access to 4G or faster networks, many remote and rural regions still lag behind in terms of internet coverage. A report from the American Hospital Association shows that 34 million Americans do not have access to satisfactory broadband [22]. The existing Federal Communication Commission program that supports the expansion of broadband is criticized as cumbersome and insufficient to fill the financial gap of increasing broadband access in rural areas [22]. Previous studies have found that telehealth is an effective tool to treat a large group of patients in disaster response [23] and that Wi-Fi and cellular service are key to the successful implementation of telemedicine [19]. The poor coverage may limit, for example, the quality of video conferences between patients and health care workers, or even between health care workers from remote areas. Even in developed health care facilities or regions, the communication demands during the COVID-19 pandemic may still impose a heavy load on the hospitals' network, thus hindering telehealth capabilities and requiring immediate technical attention. One solution to improve telehealth use could be to deliver some data using 4G as well as 2G and 3G networks [24], which could ease the burden on the network.

The COVID-19 pandemic may have also changed the environment wherein the patient usually uses telehealth. The environment in which patients interact with telehealth technology may be suboptimal. The shelter-in-place orders compelled people to stay in their residential living spaces. The lighting, noise level, and airflow in residential living spaces may not be ideal for medical consultation via telemedicine. For example, childcare and at-home responsibilities may interfere with the interaction with providers via telemedicine, especially regarding sensitive issues. Such environmental factors are less often explored by studies but are still demanded important for satisfactory telehealth use [16].

Tasks

Telehealth can facilitate the delivery of clinical and nonclinical services [25], both of which are essential during the COVID-19 pandemic. Telehealth-enabled clinical services usually consist of live, video-based patient visits, store-and-forward consultations (eg, patients measure their body temperature at home and care providers evaluate the information in the remote setting), remote monitoring (eg, electronic intensive care unit [e-ICU] [13]), messages sent through phone or a patient portal, and phone calls [25,26].

The widespread adoption of telehealth to deliver care during the COVID-19 pandemic has changed the care delivery protocols [27]. Patients are expected to collaboratively fill systemic (eg, navigating an unfamiliar method of accessing care), informational (eg, primary care physicians cannot visually examine the patients if the consultation is realized via messages or phone calls, and their diagnosis would only be based on verbal descriptions, which is filled in by patients), or procedural (eg, recording their own vital signs prior to video consultation or store-and-forward consultation) gaps. As patients are required to take more responsibility with telehealth, they could feel overwhelmed and disoriented about navigating the rapidly changing system of care. Thus, it is vital to ensure the design of a telehealth-mediated health care system is centered on patients' needs and experiences.

Current telehealth practices have also disrupted care providers' workflow and work content [28,29]. In a report describing a Veterans Affairs physician's day of tele-interacting with their patients in the era of the COVID-19 pandemic, the provider was frustrated that telehealth does not allow them to quickly grasp important peripheral information of patients, such as their comportment and facial expressions, which in-person visits allow for [29]. The peripheral information is essential to providers particularly for older patients or those with various underlying health conditions, that is, groups that are the most vulnerable to COVID-19. This is not an isolated example, and there are more care providers affected that need to make the quick switch to telemedicine to be compliant with the new care policies during the COVID-19 pandemic. This introduces extreme stress into the health care system, especially when additional training is often necessary. Above all, telehealth as a protective method for health care workers during the pandemic is mostly leading to the positive outcomes, but its negative effects should also be addressed. For example, it is advised that establishing routine tele-follow-up communications is one way to help attenuate the negative effects of disruption, as it keeps clinicians informed of their care decision results and enables them to maintain the continuity of care [30].

Organization

During the COVID-19 pandemic, many facilities were required to form new teams that were specifically designated to tackle all COVID-19-related activities, including care coordination. For instance, an academic medical center in San Diego formed an "Ambulatory COVID Team (ACT)" consisting of seven care providers, including physicians, nurses, epidemiology experts, and administrative officers [30]. Furthermore, the guidelines for crisis standards of care at short-term inpatient acute care

facilities, published by individual states, urges all health care facilities to assemble a committee that is designated to review and implement guidance during the COVID-19 crisis [31]. Such new teams and committees would change the teamwork dynamic within their health care system.

Considering e-ICU programs as an example of telehealth, several programs provided services to allow physicians and nurses to remotely monitor patients in ICUs across several hospitals [13]. The services from these institutions can reduce the burden on and needs of the health care workforce in local hospitals and may be more cost-effective than the traditional ICU setting. The challenges remain in terms of how remote clinicians communicate, collaborate, and coordinate with onsite health care workers to deliver timely and necessary care to patients that are compliant with the safety standards. The overall management and organization of ICU may require further analysis as to who should be accountable for patient safety.

In addition to the numerous changes telehealth could possibly contribute to the teamwork dynamics, it could also play a role in resource reallocation within the system. Resources in health systems usually include labor resources (ie, a variety of care providers and administrative staff), equipment resources (ie, ventilator, PPE, and computers), information resources (ie, patient information), and funding resources (ie, payment and reimbursement).

Telehealth can conserve valuable labor resources and maximize the use of available human resources by (1) protecting health care providers from potential exposure to COVID-19; (2) allowing health care providers with suspected exposure to COVID-19 to continue working, who may otherwise have to be self-isolated [13]; (3) integrating labor resources across different systems (eg, e-ICU can reduce the onsite labor resource requirement by using centralized patient monitoring [13]). Ideally, telemedicine can help out-of-state providers to fill in the local shortage of health care workforce economically and promptly [19]; however, state-based physician licensure can hinder the use of telemedicine to coordinate the cross-state response to a natural disaster such as COVID-19 pandemic [26]. Fortunately, the pandemic has effected changes to several policies, as the federal and state governments have modified or waived certain policies to facilitate the broad application of telehealth [30].

Telehealth use was mostly restricted to patients living in remote areas or staying in the health care facilities [22]; therefore, most patients, even if they wanted telehealth services, did not have many options to do so, given the billing and insurance coverage concerns associated with its use. One report listed reimbursement problems as one of the barriers to the use of telehealth [8]. In the United States, a recent survey revealed that the District of Columbia and 42 out of 50 states have enacted some telehealth commercial insurance coverage policy [32], and only 35 states together with the District of Columbia have some sort of parity law [22], which direct insurance providers to cover telehealth services the same way as they would cover in-person care services. However, in many states, the details of reimbursement policy of telehealth are still vague as payment parity is unclear as well. The payment parity means that

telehealth services should be reimbursed to the same extent as how traditional in-person services are reimbursed. Given the special circumstances of the COVID-19 pandemic, wherein many fees are subsidized or waived, parity payment is not a significant concern at this stage but telehealth insurance coverage is still a dominating issue. As urban dwellers are more in need of telehealth due to the higher likelihood of spread of the virus within areas of relatively higher population density [30], the traditional telehealth reimbursement policies would pose as a barrier to applying telehealth during the COVID-19 pandemic. In 2018, Duffy and Lee [20] suggested that providers need to actively redesign the care models and that the payment system will evolve along with it. Fortunately, this is no longer the case. Current Medicare coverage in the United States has removed the rural and site limitations and allows patients residing in any location to get covered for their telehealth use [33].

The pandemic-driven telehealth uptake also heightened the information flow problem more than ever before. A COVID-19 care management pathway enabled by telehealth can connect many health care entities for triaging, screening, and treatment through telehealth or onsite outpatient visits, specimen collection (onsite or drive-through), clinical testing laboratories, follow-up with primary care or appropriate care providers, and inpatient care [34]. Information flow among these entities is often fragmented due to a plethora of regulations and laws such as the Health Information Technology for Economic and Clinical Health Act and Health Insurance Portability and Accountability Act (HIPAA) [34]. The multiple overlapping federal and state laws that intentionally protect health information located in different information systems now unsurprisingly also make it onerous for care providers and patients to use telehealth to exchange COVID-19-related information [35]. Therefore, the difficulty of integrating patient health information across entities needs to be addressed for effective telehealth services. Improving interoperability between various information systems and enhancing electronic health record as a one-stop information hub may be one potential solution [34].

Processes

The clinical care processes of COVID-19 typically consist of four stages: screening, testing, treatment, and recovery. During the screening stage, forward triage is deemed as an important practice to relieve the intake pressure on the health care facility's front end [13]. Ideally, forward triage is done through telehealth

where initial risk assessment and patient counseling are conducted remotely [34]. This would give patients quicker access to care while keeping low-risk patients away from the overwhelmed health care system and reducing unnecessary exposure for patients and care providers. In addition to the forward triage, tele-intake is also a good approach to reduce exposure risks for some in-person visits if deemed necessary [13]. It is noteworthy that the use of telehealth may not reduce the overall time that patients spend in the health care system, starting from the initial contact with the health care system until their last contact, because telehealth may not address the bottlenecks of the entire treatment management process that cause delays. For example, forward triage can reduce patients' time of accessing care, but they may still need to wait for a hospital bed during their actual in-person visit. One study found that tele-intake can increase the rate of leaving without treatment completion and that tele-intake only functions best when the health care system capacity levels up accordingly [36].

While telehealth had manifested its potential in allowing patients quicker access to care, it also imposed a higher requirement for care providers' time management. A traditional busy lobby usually made it easier to accept if the physicians were late to the appointments; however, patients waiting alone on a web-based platform and not being able to see the bustle on the side of care providers could make the care experience less patient-centered. Hence, an ideal telehealth system design would allow care providers to better engage patients and improve their care experience before and after the televisit.

In terms of other processes that support care processes, telehealth may exhibit different effects. For example, with fewer in-person visits, the stress and demand of repetitive environment disinfection could be relatively relieved. However, telehealth could also impose extra challenges of integrating, maintaining, and transferring of patient information.

Outcomes

Regulation and policy changes that have come into effect during the pandemic may be perceived as the driving force for the large-scale uptake of telehealth. However, for longer-term sustainability, performance-based outcome metrics are needed to assess the impact of telehealth on health systems. A few studies have made initial attempts to apply existing performance metrics to assess telehealth implementation [36,37]. The outcome measures we propose (Table 2) can help guide future work in optimizing and scaling telehealth implementation.

Table 2. Potential outcome measures of telehealth-enabled care.

| Outcome level and dimension | Potential outcome measures |
|-----------------------------|--|
| Patient outcome | |
| Patient safety | <ul style="list-style-type: none"> • Diagnostic errors (compared to in-person visits) • Hospitalization rate • ICU^a admission rate • Intubation rate • Mortality rate (general and ICU) • Readmission rate • Health care-associated infections |
| Care quality | <ul style="list-style-type: none"> • Left without being seen • Door-to-provider and door-to-disposition times • Left without treatment complete • Left against medical advice • Left without treatment [36] |
| Employee outcome | |
| Work safety | <ul style="list-style-type: none"> • Work-associated infections • PPE^b sufficiency |
| Work quality | <ul style="list-style-type: none"> • Work stress and clinician burnout • Work efficiency |
| Organizational outcome | <ul style="list-style-type: none"> • Staff turnover rate • Policy implementation performance • Finance health index (before and after the COVID-19 pandemic) |

^aICU: intensive care unit.

^bPPE: personal protective equipment.

Conclusions

The COVID-19 pandemic has thrust telehealth solutions into the front line of health care despite significant barriers to its effective implementation and optimization. There are significant benefits to utilizing telehealth, namely providing enhanced safety options for patients and health care providers during the pandemic and introducing the potential to enhance efficiency and convenience in the future. However, challenges with

telehealth implementation arising in different domains of health care work system and processes that potentiate disruption to care delivery, worsen disparities in health care, and provoke changes from different levels within the health care industry, still need to be addressed. Future efforts should therefore address these barriers to implementation by redesigning telehealth solutions via a systematic approach such that health care systems can mitigate the negative effects of telehealth and seamlessly realize the benefits and enhanced safety that telehealth provides.

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Conflicts of Interest

None declared.

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Abbreviations

e-ICU: electronic intensive care unit

ICU: intensive care unit

PPE: personal protective equipment

SEIPS: Systems Engineering Initiative for Patient Safety Model

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Original Paper

Patient Satisfaction and Trust in Telemedicine During the COVID-19 Pandemic: Retrospective Observational Study

Sharon Orrange^{1*}, MD, MHS; Arpna Patel^{1*}, MD; Wendy Jean Mack^{1*}, PhD; Julia Cassetta^{1*}, MD

Keck School of Medicine of USC, University of Southern California, Los Angeles, CA, United States

*all authors contributed equally

Corresponding Author:

Sharon Orrange, MD, MHS

Keck School of Medicine of USC

University of Southern California

1975 Zonal Avenue

Los Angeles, CA, 90033

United States

Phone: 1 323 442 5100

Fax: 1 310 272 8206

Email: sharon.orrange@med.usc.edu

Abstract

Background: Los Angeles County is a hub for COVID-19 cases in the United States. Academic health centers rapidly deployed and leveraged telemedicine to permit uninterrupted care of patients. Telemedicine enjoys high patient satisfaction, yet little is known about the level of satisfaction during a crisis and to what extent patient- or visit-related factors and trust play when in-person visits are eliminated.

Objective: The aim of this study is to examine correlates of patients' satisfaction with a telemedicine visit.

Methods: In this retrospective observational study conducted in our single-institution, urban, academic medical center in Los Angeles, internal medicine patients aged ≥ 18 years who completed a telemedicine visit between March 10th and April 17th, 2020, were invited for a survey ($n=1624$). Measures included patient demographics, degree of interpersonal trust in patient-physician relationships (using the Trust in Physician Scale), and visit-related concerns. Statistical analysis used descriptive statistics, Spearman rank-order correlation, and linear and ordinal logistic regression.

Results: Of 1624 telemedicine visits conducted during this period, 368 (22.7%) patients participated in the survey. Across the study, respondents were very satisfied (173/365, 47.4%) or satisfied ($n=129$, 35.3%) with their telemedicine visit. Higher physician trust was associated with higher patient satisfaction (Spearman correlation $r=0.51$, $P<.001$). Visit-related factors with statistically significant correlation with Trust in Physician score were technical issues with the telemedicine visit ($r=-0.16$), concerns about privacy ($r=-0.19$), concerns about cost ($r=-0.23$), satisfaction with telemedicine convenience ($r=0.41$), and amount of time spent ($r=0.47$; all $P<.01$). Visit-related factors associated with patients' satisfaction included fewer technical issues ($P<.001$), less concern about privacy ($P<.001$) or cost ($P=.02$), and successful face-to-face video ($P<.001$). The only patient variable with a significant positive association was income and level of trust in physician ($r=0.18$, $P<.001$). Younger age was associated with higher satisfaction with the telemedicine visit ($P=.005$).

Conclusions: There have been calls for redesigning primary care after the COVID-19 pandemic and for the widespread adoption of telemedicine. Patients' satisfaction with telemedicine during the COVID-19 pandemic is high. Their satisfaction is shaped by the degree of trust in physician and visit-related factors more so than patient factors. This has widespread implications for outpatient practices and further research into visit-related factors and the patient-provider connection over telemedicine is needed.

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KEYWORDS

telemedicine; patient satisfaction; COVID-19; health services research; health policy; health care delivery; physicians; medicine

Introduction

On March 11, 2020, the World Health Organization declared the COVID-19 outbreak a pandemic; thereafter, telemedicine—particularly video consultation—was promoted and scaled up to reduce the risk of transmission [1,2]. A few months later, Los Angeles became the county with the highest number of COVID-19 cases in the United States [3,4]. To prioritize public health, our academic health center rapidly deployed and leveraged telemedicine in response to the COVID-19 pandemic, permitting uninterrupted care of our patients [5]. We transitioned all clinic encounters as of March 16, 2020, to telemedicine, defined here as synchronous video or telephone visits [6,7].

Studies have shown that telemedicine visits enjoy high patient satisfaction [8,9]. Still, little is known about patient satisfaction with their primary care provider during a pandemic when patients have little choice but to seek remote care. Historically, correlates of patient satisfaction with telemedicine represent patients who have chosen that platform and thus are skewed toward a younger, female, and underinsured or uninsured population [10,11]. Additionally, patient satisfaction with direct-to-consumer telemedicine has been assessed with little or no previous doctor-patient relationship or coordination with the patients' primary care provider [12]. Patient trust in their provider, an essential foundation for fostering patient satisfaction, has not been well studied in this type of remote care setting [13].

Rapid implementation of telemedicine within practices has been proposed to properly care for patients during the pandemic and beyond [14,15]. With the tremendous advances in telemedicine since COVID-19, determining factors correlated with satisfaction carries widespread implications for outpatient medicine and efforts to establish a framework for satisfying telemedicine visits. These findings are crucial for providers in adopting telemedicine as an element of the patient care continuum.

We captured 6 weeks of telemedicine visits in our primary care practice to explore the relationship between trust and patient satisfaction during a telemedicine visit, which has received little attention [16-18]. We examined whether patient factors, visit-associated factors, and the degree of "trust in provider" contributed to a satisfying telemedicine visit. We hypothesized that patient satisfaction with a telemedicine visit would be positively related to the degree of trust in the provider, patient-specific factors, and ease of use of the telemedicine platform.

Methods

Keck Medical Center is a large academic medical center located in Los Angeles. Inpatient services are provided at our institution at Keck Medical Center and USC Verdugo Hills Hospital, while outpatient services are provided at Keck Medical Center Outpatient facilities; both institutions share the same providers.

Data Source

Upon providing informed consent, the respondent was invited to complete a questionnaire provided by electronic survey. To explore the degree to which "trust in physician" correlates with satisfaction with telemedicine, we used a previously validated measure, the 11-question Trust in Physician Scale [19], to assess interpersonal trust in patient-physician relationships. Responses were scored on a 5-point Likert scale and higher scores indicated higher levels of trust (scale range 11-55).

Telemedicine visit-related issues and concerns including cost, privacy, convenience, technical issues, and time were assessed using a 5-item Likert scale. Responses ranged from 1-5 and higher scores indicated higher levels of agreement/satisfaction.

Satisfaction with the telemedicine visit was measured using the statements "I look forward to using telehealth in the future" (yes/no) and "To what extent were you satisfied with your visit?" (5-item Likert scale).

Respondents were also asked several questions about their demographics and health status.

Study Population

We performed a retrospective study of patients aged 18 years and older who had one or more telemedicine visits with a provider in the internal medicine department at the Keck Medical Center between March 10th and April 17th, 2020. This timing corresponds with a Keck Medical Center mandate to shift the majority of outpatient care from in-person to telemedicine visits. A total of 1744 patients had an encounter with our internal medicine providers during that time, and a link to a survey was successfully emailed to 1624 patients (93%). Data were collected in the fall of 2020. To be eligible to participate, the respondent had to have a telemedicine visit with one of our primary care providers. With a final sample size of 368 responders (22.7%), the attained sample size provided 80% statistical power to detect correlations of 0.14 and higher. All patients during the study period were invited to a video-enabled telehealth visit; of the 368 responders, 284 (77.4%) used video with their telehealth visit and the rest were telephone consultations. The study database in REDCap used the survey feature; all surveys were completed anonymously, and no personal health information or personally identifiable information on survey respondents was collected, in compliance with the Health Insurance Portability and Accountability Act (HIPAA). Nonresponders were similar in gender to responders (60.3% female versus 64.4% female), but responders were older than nonresponders by an average of 4.5 years ($P < .001$).

Statistical Analysis

Descriptive statistics were used to summarize visit-related concerns, patient characteristics, and satisfaction with the telemedicine visit. Variables were summarized as frequency and percentages for categorical variables and median and IQR for continuous variables.

The association of the Likert scale satisfaction item with trust in physician was evaluated with a Spearman rank-order correlation. The median (IQR) Trust in Physician Scale score is presented by level of patient satisfaction.

Associations of patient- and visit-related factors with Trust in Physician score and patient satisfaction used Spearman rank-order correlation, linear regression, and ordinal logistic regression (ordinal patient satisfaction dependent variable). Patient- and visit-related factors found in a linear regression analysis to be associated with the Trust in Physician score were included as independent variables to obtain an estimate and test of the adjusted association of trust with satisfaction with the telemedicine encounter.

Results

Preliminary Analysis

A link to a survey was emailed to 1624 patients; there were 368 respondents. The characteristics of the sample (N=368) are described in [Table 1](#). The sample was primarily female and White, with a mean age of 55.8 (SD 16.0) years. Respondents evaluated their current health as fair to good.

Across the study, respondents were very satisfied (173/365, 47.4%) or satisfied (n=129, 35.3%) with their telemedicine visit, and 77.3% (279/361) reported that they “look forward to using telehealth in the future.” [Table 2](#) describes the visit

characteristics of the sample. Respondents tended not to worry about privacy or the cost of the telemedicine visit. The majority of patients (284/367, 77.4%) used video with their telehealth visit, while the rest were telephone consultations. Face-to-face video rather than telephone alone was preferred by most respondents, with 67.7% (243/359) strongly agreeing/agreeing it was important. Almost one-third of patients (114/365, 31.3%) had technical issues during the visit, yet 63 were resolved during the telemedicine visit. Notably, despite technical challenges, the convenience of telehealth was supported by 55.7% (204/366) and 32.8% (n=120) of patients who strongly agreed and agreed the telehealth visit was convenient, respectively. There was high satisfaction among our respondents with the amount of time spent and 90.1% (327/363) strongly agreed or agreed that the amount of time spent with the provider was adequate. Patients did not appear to have privacy concerns, with 28.8% (105/365) strongly disagreeing and 40% (n=146) disagreeing that they were “concerned about privacy.”

A summary of results from respondents to the 11-point Trust in Physician Scale appears in [Table 3](#). Respondents overwhelmingly agreed with the statement “I trust my doctor’s judgments about my medical care” and that their doctor “is a real expert in taking care of medical problems.”

Table 1. Patient characteristics.

| Characteristics | Values |
|---------------------------------------|------------|
| Age in years (n=365), median (IQR) | 57 (43-68) |
| Hispanic (n=366), n (%) | 96 (26.2) |
| Race (n=348), n (%) | |
| White | 262 (70) |
| Black or African American | 25 (7.2) |
| American Indian or Alaskan Native | 7 (2) |
| East Asian | 28 (8.1) |
| Southeast Asian | 14 (4) |
| Asian Indian | 3 (0.9) |
| Native Hawaiian or Pacific Islander | 3 (0.9) |
| Some other race | 32 (9.2) |
| Female (n=364), n (%) | 239 (66) |
| Education (n=364), n (%) | |
| Less than high school | 10 (2.8) |
| High school degree or equivalent | 14 (3.9) |
| Some college but not degree | 67 (18.4) |
| Bachelor's degree | 109 (30) |
| Graduate degree | 164 (45.1) |
| Current health (n=365), n (%) | |
| Excellent | 46 (12.6) |
| Good | 196 (53.7) |
| Fair | 98 (26.9) |
| Poor | 25 (6.9) |
| Income in US \$ (n=364), n (%) | |
| 0-19,999 | 29 (8) |
| 20,000-39,999 | 17 (4.7) |
| 40,000-59,999 | 22 (6) |
| 60,000-79,999 | 37 (10.1) |
| 80,000-99,999 | 24 (6.6) |
| 100,000-119,999 | 21 (5.6) |
| 120,000-139,999 | 21 (5.6) |
| 140,000-159,999 | 21 (5.6) |
| 160,000-179,999 | 11 (3) |
| 180,000-199,999 | 13 (3.6) |
| 200,000 or more | 78 (21.4) |
| Prefer not to answer | 70 (19.2) |

Table 2. Visit characteristics.

| Characteristics | Participants, n (%) | Median (IQR) |
|---|---------------------|------------------|
| Used video with your telehealth visit (n=367) | 284 (77.4) | N/A ^a |
| Did you experience significant technical issues before or during your visit? (n=365) | | N/A |
| Yes | 51 (14) | |
| Yes, but it was resolved during telehealth visit | 63 (17.3) | |
| No | 251 (69) | |
| What sort of technical issues did you have? (n=110) | | N/A |
| Sound was not working | 13 (11.8) | |
| Video was not working | 38 (34.5) | |
| I was able to connect, but via different telehealth sources | 32 (39.1) | |
| Other issues | 27 (24.6) | |
| The telehealth visit was convenient (n=366) | | 5 (4-5) |
| Strongly disagree | 7 (1.9) | |
| Disagree | 11 (3) | |
| Neither agree nor disagree | 24 (6.6) | |
| Agree | 120 (32.8) | |
| Strongly agree | 204 (55.7) | |
| The amount of time spent was adequate (n=363) | | 5 (4-5) |
| Strongly disagree | 5 (1.4) | |
| Disagree | 9 (2.5) | |
| Neither agree nor disagree | 22 (6.1) | |
| Agree | 134 (36.9) | |
| Strongly agree | 193 (53.2) | |
| I was concerned about privacy (n=365) | | 2 (1-3) |
| Strongly disagree | 105 (28.8) | |
| Disagree | 146 (40) | |
| Neither agree nor disagree | 63 (17.3) | |
| Agree | 28 (7.7) | |
| Strongly agree | 23 (6.3) | |
| Having face-to-face video was important (n=359) | | 4 (3-5) |
| Strongly disagree | 7 (2) | |
| Disagree | 22 (6.1) | |
| Neither agree nor disagree | 87 (24.2) | |
| Agree | 108 (30.1) | |
| Strongly agree | 135 (37.6) | |
| I was worried how much my telehealth visit would cost (n=363) | | 2 (2-3) |
| Strongly disagree | 83 (22.9) | |
| Disagree | 114 (31.4) | |
| Neither agree nor disagree | 112 (30.9) | |
| Agree | 36 (9.9) | |
| Strongly agree | 18 (4.5) | |
| I look forward to using telehealth in the future (n=361) | 279 (77.3) | N/A |
| To what extent were you satisfied with your visit (n=365) | | N/A |

| Characteristics | Participants, n (%) | Median (IQR) |
|---|---------------------|--------------|
| Very unsatisfied | 10 (2.7) | |
| Unsatisfied | 14 (3.8) | |
| Neutral | 39 (10.7) | |
| Satisfied | 129 (35.3) | |
| Very satisfied | 173 (47.4) | |
| Did you recover from your illness? (n=312) | | N/A |
| Yes | 12 (3.9) | |
| Yes, but I required more than one telehealth visit | 12 (3.9) | |
| No, I was seen in an urgent care clinic/emergency room | 70 (22.4) | |
| No, I was sent to the Keck Medical evaluation tent or Evaluation and Treatment Center | 218 (69.9) | |

^aN/A: not applicable.

Table 3. Trust in Physician Scale responses.

| Statements | Participants, n (%) | Median (IQR) |
|--|---------------------|--------------|
| I doubt my doctor really cares about me as a person (n=366) | | 1 (1-2) |
| Strongly disagree | 202 (55.2) | |
| Disagree | 104 (28.4) | |
| Neither agree nor disagree | 40 (10.9) | |
| Agree | 8 (2.2) | |
| Strongly agree | 12 (3.3) | |
| My doctor is usually considerate of my needs and puts them first (n=365) | | 5 (4-5) |
| Strongly disagree | 7 (1.9) | |
| Disagree | 4 (1.1) | |
| Neither agree nor disagree | 32 (8.8) | |
| Agree | 131 (35.9) | |
| Strongly agree | 191 (52.3) | |
| I trust my doctor so much I always try to follow his/her advice (n=365) | | 4 (4-5) |
| Strongly disagree | 6 (1.6) | |
| Disagree | 2 (0.5) | |
| Neither agree nor disagree | 33 (9) | |
| Agree | 152 (41.6) | |
| Strongly agree | 172 (47.1) | |
| If my doctor tells me something is so, then it must be true (n=363) | | 4 (3-4) |
| Strongly disagree | 8 (2.2) | |
| Disagree | 23 (6.3) | |
| Neither agree nor disagree | 117 (32.2) | |
| Agree | 153 (42.2) | |
| Strongly agree | 62 (17.1) | |
| I sometime distrust my doctor's opinion and would like a second one (n=362) | | 2 (2-3) |
| Strongly disagree | 82 (22.7) | |
| Disagree | 152 (42) | |
| Neither agree nor disagree | 85 (23.5) | |
| Agree | 35 (9.7) | |
| Strongly agree | 8 (2.2) | |
| I trust my doctor's judgements about my medical care (n=362) | | 4 (4-5) |
| Strongly disagree | 5 (1.4) | |
| Disagree | 3 (0.8) | |
| Neither agree nor disagree | 25 (6.9) | |
| Agree | 167 (46.1) | |
| Strongly agree | 162 (44.8) | |
| I feel my doctor does not do everything he/she should for my medical care (n=363) | | 2 (1-2) |
| Strongly disagree | 148 (40.7) | |
| Disagree | 137 (37.7) | |
| Neither agree nor disagree | 44 (12.1) | |
| Agree | 24 (6.6) | |
| Strongly agree | 10 (2.8) | |

| Statements | Participants, n (%) | Median (IQR) |
|---|---------------------|--------------|
| I trust my doctor to put my medical needs above all other considerations when treating my medical conditions (n=362) | | 4 (4-5) |
| Strongly disagree | 4 (1.1) | |
| Disagree | 8 (2.2) | |
| Neither agree nor disagree | 47 (13) | |
| Agree | 151 (41.7) | |
| Strongly agree | 152 (42) | |
| My doctor is a real expert in taking care of medical problems (n=363) | | 4 (4-5) |
| Strongly disagree | 3 (0.8) | |
| Disagree | 4 (1.1) | |
| Neither agree nor disagree | 51 (14) | |
| Agree | 154 (42.2) | |
| Strongly agree | 151 (41.6) | |
| I trust my doctor to let me know if a mistake was made about my treatment (n=362) | | 4 (4-5) |
| Strongly disagree | 4 (1.1) | |
| Disagree | 8 (2.2) | |
| Neither agree nor disagree | 54 (14.9) | |
| Agree | 158 (43.7) | |
| Strongly agree | 138 (38.1) | |
| I sometimes worry that my doctor may not keep the information we discuss totally private (n=365) | | 1 (1-2) |
| Strongly disagree | 199 (54.5) | |
| Disagree | 115 (31.5) | |
| Neither agree nor disagree | 47 (12.9) | |
| Agree | 3 (0.8) | |
| Strongly agree | 1 (0.3) | |
| Physician trust total score ^a (n=345) | | 46 (42-51) |

^aPhysician trust total score generated by the sum of 11 items from the physician trust survey. Highest possible score=55; mean 45 (SD 6.5).

Trust in Physician and Satisfaction With Telemedicine Visit

Higher physician trust was associated with higher patient satisfaction with the telemedicine visit. Results of the Spearman correlation indicated that there was a significant positive association between the degree of patients' trust in physician and satisfaction with their telemedicine visit ($r=0.51$, $P<.001$).

Patient Factors and Trust in Physician

Overall, patient factors including age ($r=-0.01$, $P=.81$), level of education ($r<0.01$, $P=.99$), and current health status ($r=-0.01$, $P=.78$) were not significantly correlated with level of trust in their physician. There was, however, a significant positive association between income and level of trust in physician ($r=0.18$, $P<.001$).

Visit-Related Factors and Trust in Physician

In contrast to patient factors, several visit-related factors showed a significant correlation with Trust in Physician score. Respondents who did not have technical issues ($r=-0.16$,

$P=.002$), concerns about privacy ($r=-0.19$, $P<.001$), or concerns about the cost ($r=-0.23$, $P<.001$) had a higher degree of trust in their physician. Those who agreed face-to-face video was important ($r=0.23$, $P<.001$), liked the convenience ($r=0.41$, $P<.001$), and were satisfied with the amount of time spent ($r=0.47$, $P<.001$) also showed a higher degree of trust in their physician.

Patient Factors and Satisfaction With Telemedicine Visit

Patient factors including gender ($P=.67$), education ($P=.82$), income ($P=.14$), and current health ($P=.18$) were not associated with satisfaction with their telemedicine visit. Age was the only significant factor associated with satisfaction, with a younger median age of 54 (IQR 42-64) years among those who were very satisfied compared to a median age of 60 (IQR 50-69) years among those who were unsatisfied or neutral (likelihood ratio $P=.005$ with ordinal logistic regression).

Visit-Related Factors and Satisfaction With Telemedicine Visit

Evaluated by ordinal logistic regression, all visit-related factors were associated with patient satisfaction with their telemedicine visit. Fewer technical issues ($P<.001$), acknowledging the convenience ($P<.001$), appreciating the amount of time spent ($P<.001$), fewer concerns about privacy ($P<.001$) and cost ($P=.02$), and successful face-to-face video ($P<.001$) were all significantly associated with a satisfying telemedicine visit.

Discussion

The COVID-19 pandemic poses unique challenges to health care delivery, especially for those in primary care. Patient fear surrounding COVID-19 has disrupted patients' normative expectations toward their doctors (and vice versa), creating more complex trust relationships. Prior studies have shown patients prefer telemedicine with a doctor with whom they have an established relationship [20]. When it comes to specialist referral, trust and confidence in one's primary care provider are crucial to creating a satisfying experience [21,22].

Telemedicine, particularly video consultation, has been rapidly implemented to reduce the risk of transmission. Before this historic period, studying telemedicine satisfaction would have posed a self-selection bias, which the pandemic mostly eliminated due to institutional and patient health precautions early on. Correlates of patient satisfaction aid to inform and further educate practices adopting telemedicine and the pandemic provides a unique opportunity to evaluate those visits and factors affecting satisfaction.

Patients' trust in their physician, telemedicine services, and willingness to rely on such a health service for care during a pandemic has not previously been described. Researchers have given little attention to which factors contribute to trust in a telemedicine visit, a unique situation made more difficult during the pandemic. A previously reported study on the use of telehealth visits for anticoagulation management found trust in the technology, trust in health care professionals, and trust in the treatment affected trust in the telemedicine service [23]. The rapid transition to telemedicine requires providers and patients to transition to a new normal that includes communicating via telephone or video. For providers, this means developing skills in building trust, counseling, empathy, "modified" physical exams, and diagnosis using the telemedicine platform. Prior telemedicine studies include a level of self-selection, yet provide some insight into the importance of trust in provider for telemedicine visits. In one study, patients who chose a virtual follow-up over an in-person visit spoke of the importance of an existing doctor-patient relationship and having already had previous consultations with that same person before the follow-up video consultation [24].

Recent suggestions on fostering human connection have focused primarily on telemental health, with tips provided for enhancing virtual connections, such as being "present," identifying needs, listening, responding with empathy, and sharing information [25]. Empirical evidence in this area is sparse and achieving greater clarity about factors contributing to a satisfying

telemedicine visit would help health care providers better anticipate patients' needs.

Our study provides new insights into the reasons for a satisfying telemedicine visit when an established relationship with the provider or practice exists. Consistent with our hypothesis and using our patients' experience at the onset of the COVID-19 pandemic, we found that trust in physician, as assessed using the 11-question Trust in Physician Scale, was correlated with higher patient satisfaction in telemedicine visits. Patients who trust their doctor and try to follow his/her advice, trust their doctor's judgment about medical care, and believe their doctor will let them know if a mistake was made about their treatment were more likely to be satisfied with a telemedicine visit and wanted to use the platform again. These findings suggest a significant role in provider engagement, fostering human connection, and strengthening the patient-physician attachment. Higher physician trust was positively correlated with greater patient satisfaction with telemedicine.

Furthermore, factors related to the visit, including privacy, cost, convenience, and time, were associated with higher satisfaction and higher trust in physicians. Our findings suggest that ease of use with fewer technical issues and video-enabled visits result in higher patient satisfaction and higher trust in physician. At our institution, test calls before initial sessions help evaluate the level of technological support a patient needs for the upcoming telemedicine visit.

Our findings support a role for continued improvement in training and operational issues in telemedicine.

While the study group was mostly White, high-income, and well-educated, our study did not find evidence that patient-related factors in this sample play a significant role in trust in physician or the likelihood of a satisfying telemedicine visit. Patient income was positively associated with level of trust; this association has been reported for in-person care, where lower physician trust is seen with lower income [21]. Our study found higher income correlated with a higher level of trust in physician, which was positively associated with patient satisfaction with telemedicine. Consistent with prior research that shows younger patients, perhaps due to higher eHealth literacy, have higher acceptance of the telemedicine platform [26,27], we also found that younger age correlated with a satisfying telemedicine visit. Our predominantly younger White female population is consistent with prior studies on the acceptance of telemedicine [24,27].

This study has several limitations. First, this was a retrospective study with no comparison to in-person visit satisfaction during the same period or before the pandemic. We did not feel the pandemic's challenging situation, which did not allow for the option of in-person visits, could be compared to prior visits. As the pandemic lifts, this would be something evaluated in future studies. Previous studies on the acceptability of video consulting show that even among those who would choose that format again, face-to-face consulting was seen as the gold standard and preferred for both provider and patient for emotionally charged or more challenging consultations [24]. Second, the use of a web-based survey prevents us from recruiting patients without an email address ($n=113$, 7%), potentially leading to bias toward

respondents with higher digital literacy. Third, the response rate to the survey was lower than anticipated (368/1624, 22.7%). We suspect replying to an email survey in the early days of the pandemic presented additional challenges to our patient population who had not necessarily chosen the telemedicine platform. Fourth, respondents were significantly older than our nonresponders (55.8 years versus 51.3 years, $P < .001$), yet while our findings support younger age as a factor correlated with satisfaction with their visit, age was not correlated with trust in physician. Fifth, the Likert-based satisfaction item, although face valid, was not derived from a validated questionnaire. Lastly, as our study population was less ethnically and racially diverse than the overall United States and Los Angeles County population, we could not capture the experiences of underrepresented minorities and underserved communities.

In conclusion, this study suggests most patients are satisfied with telemedicine visits during the COVID-19 pandemic and that trust in physician correlates favorably with patient satisfaction. Trust and satisfaction are shaped by many visit-related factors, including convenience, time spent, and video-enabled encounters, rather than specific patient-related factors. Our study reinforces telemedicine as a new form of health care delivery even in times of uncertainty, supporting our hypothesis that patient satisfaction with a telemedicine visit would be positively related to the degree of trust in the provider and ease of use of the telemedicine platform. Further studies examining patient-physician relationships over telemedicine may better elucidate elements contributing to patients' trust in their physicians. With calls to promote and scale-up telemedicine in primary care, this will help develop a strategy and operational plans for providers to switch to remote patient care.

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Conflicts of Interest

None declared.

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Original Paper

Age-Related Differences in Experiences With Social Distancing at the Onset of the COVID-19 Pandemic: A Computational and Content Analytic Investigation of Natural Language From a Social Media Survey

Ryan C Moore¹, BS; Angela Y Lee¹, BA; Jeffrey T Hancock¹, PhD; Meghan C Halley², MPH, PhD; Eleni Linos³, MD, DrPH

¹Department of Communication, Stanford University, Stanford, CA, United States

²Center for Biomedical Ethics, Stanford University, Stanford, CA, United States

³Department of Dermatology, Stanford University, Stanford, CA, United States

Corresponding Author:

Jeffrey T Hancock, PhD
Department of Communication
Stanford University
450 Jane Stanford Way
Building 120, Room 110
Stanford, CA, 94305
United States
Phone: 1 650 723 5499
Email: hancockj@stanford.edu

Abstract

Background: As COVID-19 poses different levels of threat to people of different ages, health communication regarding prevention measures such as social distancing and isolation may be strengthened by understanding the unique experiences of various age groups.

Objective: The aim of this study was to examine how people of different ages (1) experienced the impact of the COVID-19 pandemic and (2) their respective rates and reasons for compliance or noncompliance with social distancing and isolation health guidance.

Methods: We fielded a survey on social media early in the pandemic to examine the emotional impact of COVID-19 and individuals' rates and reasons for noncompliance with public health guidance, using computational and content analytic methods of linguistic analysis.

Results: A total of 17,287 participants were surveyed. The majority (n=13,183, 76.3%) were from the United States. Younger (18-31 years), middle-aged (32-44 years and 45-64 years), and older (≥ 65 years) individuals significantly varied in how they described the impact of COVID-19 on their lives, including their emotional experience, self-focused attention, and topical concerns. Younger individuals were more emotionally negative and self-focused, while middle-aged people were other-focused and concerned with family. The oldest and most at-risk group was most concerned with health-related terms but were lower in anxiety (use of fewer anxiety-related terms) and higher in the use of emotionally positive terms than the other less at-risk age groups. While all groups discussed topics such as acquiring essential supplies, they differentially experienced the impact of school closures and limited social interactions. We also found relatively high rates of noncompliance with COVID-19 prevention measures, such as social distancing and self-isolation, with younger people being more likely to be noncompliant than older people ($P < .001$). Among the 43.1% (n=7456) of respondents who did not fully comply with health orders, people differed substantially in the reasons they gave for noncompliance. The most common reason for noncompliance was not being able to afford to miss work (n=4273, 57.3%). While work obligations proved challenging for participants across ages, younger people struggled more to find adequate space to self-isolate and manage their mental and physical health; middle-aged people had more concerns regarding childcare; and older people perceived themselves as being able to take sufficient precautions.

Conclusions: Analysis of natural language can provide insight into rapidly developing public health challenges like the COVID-19 pandemic, uncovering individual differences in emotional experiences and health-related behaviors. In this case, our analyses

revealed significant differences between different age groups in feelings about and responses to public health orders aimed to mitigate the spread of COVID-19. To improve public compliance with health orders as the pandemic continues, health communication strategies could be made more effective by being tailored to these age-related differences.

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KEYWORDS

COVID-19; natural language processing; public health messaging; social distancing compliance; age differences; older adults; younger adults; age; NLP; public health; elderly; youth; adult; emotion; compliance; guideline

Introduction

A signature of the COVID-19 pandemic is that the virus poses different levels of threat to individuals of different ages. In the United States, nearly three-quarters of all deaths attributable to COVID-19 have occurred in individuals ≥ 65 years of age [1]. By contrast, 4% of total deaths have been in individuals ≤ 34 years, and 22% have been in individuals between 35-64 years. As such, recent evidence suggests that older and younger individuals may differ substantially in their behavioral and attitudinal responses to COVID-19 [2]. For instance, younger people may be more likely to engage in activities that increase the risk of virus transmission, such as dining indoors or attending social gatherings, than older people.

We fielded a survey on social media early in the pandemic just as the first state-issued shelter-in-place orders were implemented in order to understand how different age groups experienced the impact of the coronavirus crisis and the extent to which they complied with self-isolation mandates. Specifically, we sought to understand older and younger peoples' experiences with the pandemic through analysis of those groups' use of language—that is, the text of their responses to open-ended survey questions. Prior work has shown that human language can provide a rich profile of how people are feeling about and experiencing daily life [3].

Understanding the public's experiences through language analysis may be particularly valuable during times of rapid change and crisis [4]. Researchers have previously analyzed language to understand how individuals are experiencing and responding to unprecedented situations, such as the present pandemic. For example, Cohn et al [5] analyzed language in online journal entries before and after the September 11, 2001, terrorist attacks in the United States and uncovered pronounced psychological changes in response to the attacks. By examining the sentiment of language and pronoun usage using computational methods, the authors found that individuals expressed more negative emotions and were less self-focused in the 2 weeks following 9/11. In addition, the analysis revealed that individuals varied considerably in the extent to which they discussed the events of 9/11 and related topics.

In this paper, we use language to explore two core questions regarding how different age groups are responding to the COVID-19 pandemic. First, how do different age groups experience the impact of the pandemic? While the pandemic is having broad-reaching effects on nearly all parts of our lives, different age groups may focus on different aspects or experience different emotions. We examine how older and

younger individuals, who face distinct levels of health risk from the virus, differentially experience those effects.

Building off the work of Cohn et al [5] on individuals' experiences of 9/11, we specifically wanted to explore 3 dimensions of language to examine differences in experiences between age groups:

1. **Sentiment:** Do older individuals express more positive or negative affect regarding their experience with the virus? Prior research has demonstrated that older individuals tend to be more emotionally positive than younger people [6,7], but with the increased risk from the pandemic, will this trend toward positivity persist?
2. **Self vs other focus:** Do different age groups, given differing levels of personal risk, vary in the extent to which they focus on themselves compared to others when discussing the virus?
3. **Topical salience:** Some virus-related topics may be more salient for some age groups than others (eg, health care or symptoms are more important for older than younger individuals).

More formally, we ask the following research question (RQ):

RQ1. How do age groups differ in how they use emotional language, self-other focus, and topical salience when describing their experience during the onset of the pandemic?

Given their differential levels of health risk, we also examined whether individuals of different age groups differed in noncompliance with the health mandates of social distancing and self-isolation. Reporting on the pandemic has drawn attention to COVID-19 clusters caused by noncompliance among communities of different ages, such as outbreaks linked to parties on college campuses and large gatherings at events like weddings [8,9]. In addition to obtaining base rates of noncompliance by age group by surveying participants about their adherence to health mandates, analyzing the language from individuals' open-ended responses allows us to explore the specific reasons people provide for not complying more often with social distancing recommendations, which have been demonstrated to be effective at slowing the spread of viral infections such as COVID-19 [10,11]. More formally, we ask the following:

RQ2. What were the rates and reasons for noncompliance with social distancing guidelines at the onset of the pandemic by age group?

In the context of public health messaging, understanding the language individuals use to describe their health-related

thoughts, feelings, and actions is essential to developing effective, scalable communication strategies for different groups who may face different levels of risk or who may behave differently in the face of a major health episode such as a pandemic [12,13]. As can be seen by increasing numbers of young people breaking social distancing protocols, more tailored interventions may be needed to communicate more effectively with individuals at different levels of health risk. Understanding how the public conceptualizes and experiences the COVID-19 health threat is crucial for public health measures requiring citizens to comply with unprecedented behavioral changes. The goal of this paper is to explore age-related differences in the experience of the pandemic (RQ1) and in peoples' noncompliance with COVID-19 prevention measures (RQ2).

Methods

Recruitment

We recruited a convenience sample of individuals impacted by the COVID-19 pandemic by posting our survey online from March 14-23, 2020. In order to maximize responses, we posted our call for respondents on Twitter, Facebook, and Nextdoor. Upon seeing recruitment materials for our study on social media, individuals could elect to participate in our study. The survey included a total of 21 questions including demographics, the impact of COVID-19 on individuals' daily life, actions taken in regard to COVID-19, and difficulties faced related to the pandemic [14]. The study was approved by the authors' institution's Institutional Review Board.

Statistical Analysis

Our first research question examined how individuals' language about their experience with the pandemic, including expressed sentiment, self or other focus, and topical salience, differed across age groups. To do this, we analyzed open-ended responses to the survey-question, "Tell us how the coronavirus crisis is impacting your life" using Linguistic Inquiry and Word Count (LIWC), a well-validated and widely used computerized text analysis program [15]. LIWC counts the number of words in a variety of psychological (eg, positive or negative emotion terms), topical (eg, family-related terms, work-related terms), and part of speech (eg, pronouns, adverbs) categories that appear in a given text relative to all the words in that text. To further explore topical focus in people's descriptions of the impact of COVID-19, we identified themes in open-ended responses for each age group using the meaning extraction method, which relies on principal component analysis (PCA) of content words in language corpora [16]. Data were processed with the Meaning Extraction Helper software to remove function words (ie, prepositions) and words with low base rates (present in <5% of responses), and calculate whether content words (ie, nouns, verbs) were present (coded as "1") or absent (coded as "0") within a response [17]. We then conducted separate PCAs on the responses for each of the four age groups.

Our second research question explored rates and reasons for noncompliance with social distancing and isolation orders by

age group. Overall rates of compliance and noncompliance were calculated by examining responses to questions asking whether participants were social distancing and isolating as much as possible. To investigate the reasons for noncompliance, participants were asked to select from a list of preselected reasons (eg, not being able to miss work), with the option to write in another reason. We conducted a thematic content analysis to identify, analyze, and report themes in these responses (Multimedia Appendix 1). This process was conducted by 2 independent raters with good interrater reliability (Cohen $\kappa=0.76-0.81$).

Results

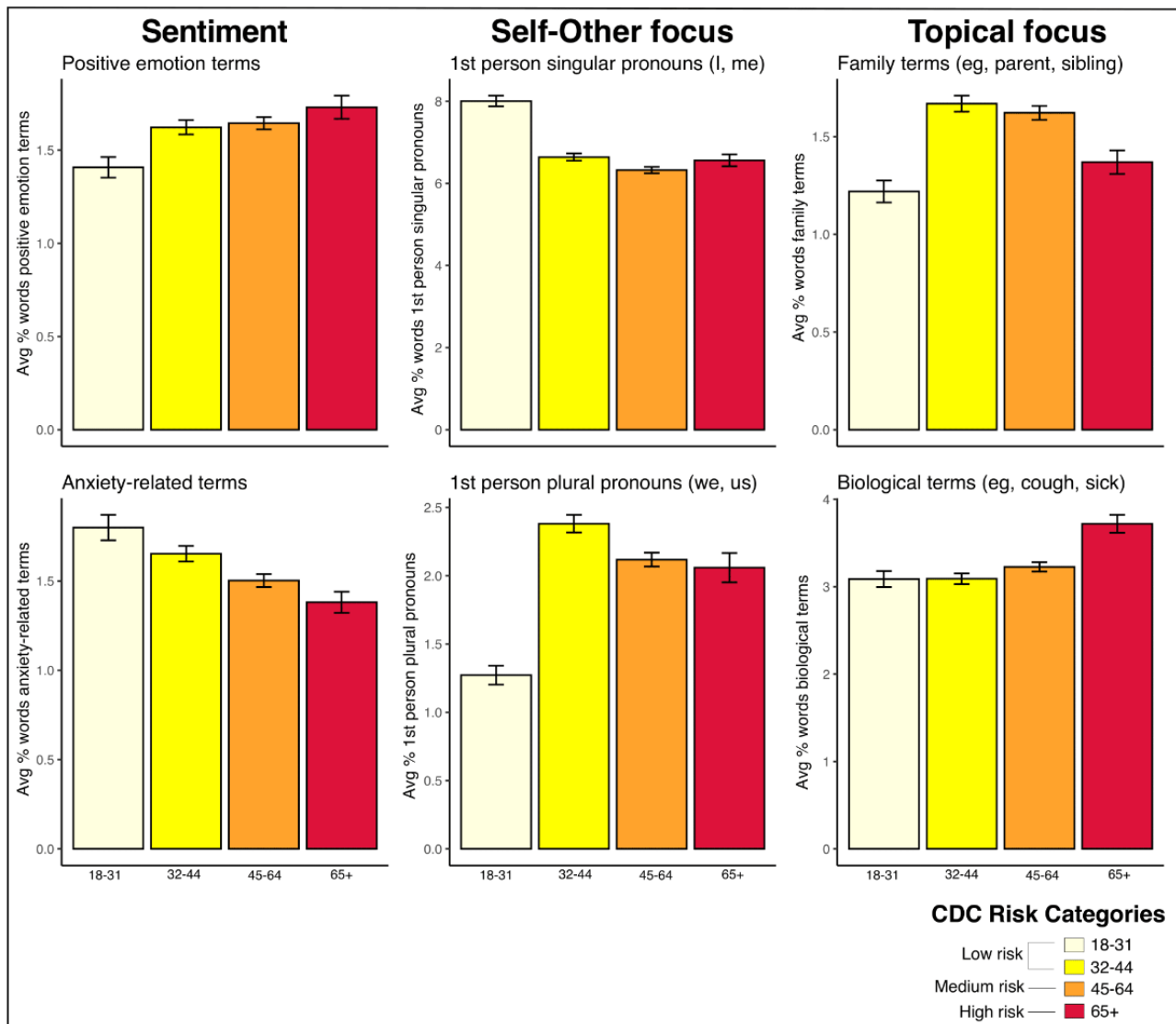
Participant Demographics

We collected a total of 17,687 responses in 9 days. We excluded 400 individuals from our data set who did not provide information on age as this was integral to all of our analyses. Thus, the resulting data set consisted of 17,287 individuals. The mean age of the sample was 45.5 years, with 16.4% (n=2905) of the sample aged 18-31 years, 34.2% (n=6054) aged 32-44 years, 36.3% (n=6417) aged 45-64 years, and 10.8% (n=1911) aged ≥ 65 years. These age groups are modeled after the age groups reported by the Center for Disease Control and Prevention in their summary of COVID-19 cases in the United States [18]. The majority of respondents identified as White (14,340/17,287, 83%) and were located in the United States (13,183/17,287, 76.3% provided a valid US zip code when asked). In addition, the sample was relatively highly educated (high school diploma or less: 426/17,287, 2.5%; some college: 2444/17,287, 14.1%; bachelor's degree: 5273/17,287, 30.5%; graduate degree: 9132/17,287, 52.8%; no information provided on educational background: 12/17,287, 0.07%).

RQ1: Language and the Impact of the COVID-19 Pandemic

Of the 17,287 total survey responses, 6573 individuals provided a response ≥ 30 words to the open-ended question "Tell us how the coronavirus crisis is impacting your life." This length cutoff was used since the LIWC development manual suggests a minimum of at least 25 words [15]. As Figure 1 shows, younger people (18-31 years) were more anxious (greater usage of anxiety-related terms), less emotionally positive (lesser usage of positive emotion terms), self-focused (greater use of first-person singular pronouns), and less concerned with family (lesser use of family-related terms), while middle-aged people were group-oriented (32-44 years; greater use of first-person plural pronouns) and focused on family (32-64 years; greater use of family-related terms). Unsurprisingly, the oldest and most at-risk group (≥ 65 years) wrote frequently about biological terms (eg, health-related topics) but were surprisingly low in anxiety (use of fewer anxiety-related terms) and emotionally positive (greater use of positive emotion terms) relative to those at lower risk (all *P* values corrected for multiple comparisons; see Multimedia Appendix 1 for the results of relevant age group comparisons).

Figure 1. Mean number of words in language categories, by age group. Age groups are modeled after the age groups reported by the Centers for Disease Control and Prevention (CDC) in their summary of COVID-19 cases in the United States [18]. Bars represent standard errors.



RQ1: Topical Salience in Describing the Impact of COVID-19

The extraction of qualitative themes from participants’ responses through the meaning extraction method allowed us to gain deeper insight into what topics people of different age groups focused on during the pandemic onset. For each of the five factors analyzed, content words were retained if their loadings were over or equal to the absolute value of .30 [16]. As seen in Table 1, people of different age groups focused on distinct aspects of their experiences. Some topics, such as acquiring essential goods and supplies (ie, groceries) and engaging in

COVID-19 prevention behaviors (ie, social distancing, hand washing), were important for people of all age groups. Other themes, however, were specific to certain age groups. The youngest age group wrote about the impact of school closures and moving home, the middle age groups wrote about the impact of COVID-19 on work and family, and the oldest age group wrote about being at high risk for COVID-19 and engaging with community services. In addition, while all groups discussed the impact of limited social interactions, young people focused on the process of adjusting, middle-aged people focused on canceled trips, and older people focused on canceled activities with family.

Table 1. Results of the principal component analysis for open-ended responses about the impact of the pandemic by age groups. Note: columns denote component numbers extracted from separate principal component analyses for each age group, subjected to Varimax rotations. Words were selected for inclusion on the component if their loading was greater than or equal to |.30|.

| Age group | Components | | | | |
|------------------------|--|---|--|--|---|
| | 1 | 2 | 3 | 4 | 5 |
| 18-31 years | | | | | |
| Theme | Concern for family | School closure | Essential supplies | Social distancing effects | Compliance |
| λ , % variance | 2.88, 3.0 | 2.78, 3.0 | 2.68, 3.0 | 2.61, 3.0 | 2.29, 2.0 |
| Word (loading) | Family (.42) Worry (.39) Sick (.39) Member (.39) Health (.37) Virus (.36) Care (.34) Due (.31) Risk (.30) Mother (.30) | Class (.69) Online (.69) Student (.48) School (.43) Cancel (.43) College (.43) Move (.42) | Store (.51) Grocery (.47) Supply (.44) Shop (.33) Clean (.33) Place (.31) Close (.31) Stock (.30) | Distance (.45) Social (.42) Walk (.41) Friend (.34) Hard (.33) Isolate (.33) Leave (.32) | Wash (.64) Hand (.63) Social (.47) Distance (.36) |
| 32-44 years | | | | | |
| Theme | COVID-19 spread | Essential supplies | Impact on work and family | Social distancing and canceled plans | School closure |
| λ , % variance | 2.84, 3.0% | 2.83, 3.0 | 2.39, 3.0 | 2.29, 2.0 | 2.11, 2.0 |
| Word (loading) | Test (.61) Symptom (.50) COVID (.45) Sick (.42) Hospital (.33) People (.31) Health (.31) | Hand (.56) Grocery (.55) Store (.54) Wash (.47) Food (.46) Shop (.37) Supply (.36) Stock (.35) Clean (.35) | School (.56) Husband (.47) Work (.45) Kid (.39) Week (.37) Close (.37) Cancel (.33) Child (.30) | Social (.53) Distance (.44) Family (.36) Cancel (.35) | Online (.66) Class (.61) College (.55) Move (.50) |
| 45-64 years | | | | | |
| Theme | School closure and family | Essential supplies | COVID-19 spread | Social distancing and canceled plans | Concern for family |
| λ , % variance | 2.75, 3.0 | 2.75, 3.0 | 2.57, 3.0 | 2.31, 2.0 | 2.27, 2.0 |
| Word (loading) | School (.60) Online (.54) College (.54) Class (.49) Student (.37) Daughter (.36) Move (.35) Close (.32) Husband (.31) High (.31) Son (.31) | Food (.57) Supply (.52) Store (.43) Hand (.43) Stock (.41) Clean (.40) Grocery (.38) Wash (.35) House (.33) | Test (.50) Symptom (.48) COVID (.48) Sick (.36) Case (.30) | Social (.60) Distance (.50) Cancel (.44) Plan (.36) Trip (.36) Activity (.31) | Worry (.39) Elderly (.36) Live (.35) Parent (.35) Concern (.33) Health (.31) Hand (-.31) Wash (-.34) |
| ≥65years | | | | | |
| Theme | Essential supplies | Community concerns | Social distancing and canceled events | High-risk status | Supporting family |
| λ , % variance | 2.89, 3.0 | 2.69, 3.0 | 2.56, 3.0 | 2.22, 2.0 | 2.22, 2.0 |

| Age group | Components | | | | |
|----------------|---------------|-----------------|----------------|-------------|--------------|
| | 1 | 2 | 3 | 4 | 5 |
| Word (loading) | Hand (.55) | Student (.35) | Cancel (.52) | Risk (.57) | Supply (.48) |
| | Wash (.54) | Community (.33) | Family (.52) | High (.49) | Food (.46) |
| | Grocery (.48) | Member (.32) | Social (.47) | Virus (.39) | Mother (.38) |
| | Store (.47) | Hospital (.32) | Plan (.43) | Sick (.35) | Job (.35) |
| | Clean (.40) | Small (.31) | Activity (.36) | | Visit (.32) |
| | Shop (.30) | Day (.31) | Event (.35) | | Find (.30) |
| | | Class (.30) | Trip (.32) | | |
| | | Time (.31) | | | |

RQ2: Rates of Compliance and Reasons for Noncompliance

Although 10,782 participants said they were not complying with social distancing and isolation orders as much as possible in a closed-ended question, analysis of their written open-ended responses revealed that approximately 30% (n=3326) were in fact in compliance with recommended health guidelines (ie, only leaving their homes to buy groceries, find essential supplies, or attend necessary medical appointments). Compliance with guidance was based on the initial guidelines present during the time of data collection, which were published just ahead of the first stay-at-home order in California (March 19, 2020) [19]. Thus, out of 17,287 survey responses, 43.1% of participants reported not fully complying (n=7456) with shelter-in-place orders. A large number of respondents (n=7416,

42.9% of total respondents) provided a reason of their own for noncompliance.

We then explored the reasons why participants did not fully comply with COVID-19 prevention guidelines, such as social distancing and self-isolation (Table 2). Of those who were noncompliant, the most common reason reported was not being able to miss work (4273/7456, 57.3%). Other reasons for not complying with health orders included not having sufficient space to self-isolate (719/7456, 9.6%), meeting mental and physical health needs (533/7456, 7.1%), feeling that other precautions were sufficient (eg, frequent handwashing; 488/7456, 6.5%), wanting to continue engaging in nonessential activities (366/7456, 4.9%), feeling that society was overreacting (339/7456, 4.5%), not believing social isolation was effective at preventing the spread of COVID (281/7456, 3.8%), needing to attend classes in person (180/7456, 2.4%), and concerns about caring for children in isolation (129/7456, 1.7%).

Table 2. Reasons for noncompliance with COVID-19 health orders by age group. Percentages were calculated as a proportion of noncompliant individuals in each age group.

| Theme | Example | Total noncompliant (n=7456), n (%) | Age category | | | |
|--|--|---------------------------------------|--------------------------------|--------------------------------|--------------------------------|-----------------------|
| | | | 18-31 years (n=1589), n (%) | 32-44 years (n=2668), n (%) | 45-65 years (n=2653), n (%) | ≥65 (n=546), n (%) |
| Cannot afford to miss work ^{a,b} | “Work is not canceled, if I don’t go I’ll lose my job.” | 4273 (57.3) | 949 (59.7) | 1689 (63.3) | 1489 (56.1) | 146 (26.7) |
| Mental and physical health needs ^b | “Total self-isolation would probably drive me to suicide.” | 533 (7.1) | 145 (9.1) | 169 (6.3) | 167 (6.3) | 52 (9.5) |
| Taking sufficient precautions ^b | “I already wash my hands regularly and cover my mouth when I cough or sneeze. I am not concerned with catching [the] virus.” | 488 (6.5) | 50 (3.1) | 115 (4.3) | 204 (7.7) | 119 (21.8) |
| No space to self-isolate ^a | — ^c | 719 (9.6) | 293 (18.4) | 246 (9.2) | 150 (5.6) | 30 (5.5) |
| Nonessential activities ^b | “Some appointments are in-person. Need to see friends sometimes.” | 366 (4.9) | 72 (4.5) | 91 (3.4) | 156 (5.9) | 47 (8.6) |
| Society is overreacting ^b | “I think the news media was making everyone panic and overreact.” | 339 (4.5) | 46 (2.9) | 95 (3.6) | 152 (5.7) | 46 (8.4) |
| Do not believe social isolation to be effective ^c | — | 281 (3.8) | 61 (3.8) | 92 (3.4) | 96 (3.6) | 32 (5.9) |
| Kids ^b | “Really hard to do with little kids - I’m reducing a lot of contact, but not all.” | 129 (1.7) | 6 (0.4) | 79 (2.9) | 39 (1.5) | 5 (0.9) |
| Have to attend in-person classes ^c | — | 180 (2.4) | 86 (5.4) | 42 (1.6) | 44 (1.6) | 8 (1.5) |

^aIndicates that this theme was identified through participants’ responses to a multiple-choice question.

^bIndicates that this theme was identified through thematic content analysis of participants’ text responses.

^cFor themes only identified through multiple-choice questions, no example response is available.

We then examined how noncompliance rates and reasons varied by age group. A chi-square test of noncompliance by age group was significant ($\chi^2_{3, 17,283}=113.56, P<.001$) and revealed that noncompliance decreased with age. The youngest group (18-31 years) had the highest rate of noncompliance while the oldest age group had the lowest. People of different age groups also differed in their reasons for noncompliance, including work ($\chi^2_{3, 17,283}=150.11, P<.001$), mental and physical health needs ($\chi^2_{3, 17,283}=14.34, P<.001$), feeling like other precautions were sufficient ($\chi^2_{3, 17,283}=38.70, P<.001$), not having space to self-isolate ($\chi^2_{3, 17,283}=116.17, P<.001$), wanting to participate in nonessential activities ($\chi^2_{3, 17,283}=5.66, P=.001$), believing that society was overreacting ($\chi^2_{3, 17,283}=4.84, P=.002$), concerns about kids ($\chi^2_{3, 17,283}=14.92, P<.001$), and having to attend classes in person ($\chi^2_{3, 17,283}=42.30, P<.001$). Frequencies of reasons for noncompliance by age group can be found in [Table 2](#).

The pattern of results suggest that while work obligations proved challenging for participants across ages, younger people

struggled more to find adequate space to self-isolate and manage their mental and physical health, middle-aged people faced more concerns regarding childcare, and older people perceived themselves as able to take sufficient precautions. Our results provide important insights into why different people fail to comply with COVID-19 prevention measures like social distancing.

Discussion

Principal Findings

Our findings from a survey of thousands of Americans early in the pandemic (March 14-23, 2020) reveal important age-related differences in how people experienced the impact of COVID-19 at the outset of the pandemic (RQ1) and in the extent to which they complied with social distancing and self-isolation orders (RQ2).

As discussed in Cohn et al [5], language can provide insight into how people are thinking and feeling during times of crisis. Examining how people of different risk levels experienced the impact of the COVID-19 pandemic and their reasons for noncompliance can inform communication and interventions

to increase compliance across the board while recognizing the unique needs of individuals from different age groups. We found that, in discussing the impact of COVID-19, younger individuals were more emotionally negative and self-focused, while middle-aged people were other-focused and concerned with family. The oldest and most at-risk group was most concerned with health-related terms but were also lower in anxiety and higher in the use of emotionally positive terms than the other, less at-risk age groups. PCA-driven topical analyses in participants' description of the impact of the pandemic on their lives supported these age-related differences. While all groups discussed necessary lifestyle changes caused by COVID-19, such as acquiring essential supplies, individuals of different age groups wrote about the impact of school closures and limited social interactions in different ways.

We also found relatively high rates of noncompliance with COVID-19 prevention measures, such as social distancing and self-isolation. However, like emotional experiences of the pandemic, rates of noncompliance varied significantly by age group. While 7456 of 17,287 respondents (43.1%) reported that they were not isolating as much as recommended, this number appears to be driven by higher rates of noncompliance among younger and middle-aged people. The youngest age group (18-31 years) had the highest rate of noncompliance, with more than half of respondents (1589/2905, 54.7%) reporting they did not isolate sufficiently. Middle-aged adults had lower rates of noncompliance (32-44 years: 2668/6054, 44.1%; 45-65 years: 2653/6417, 41.3%). The oldest age group, which faced the highest level of health risk from COVID-19, was the most compliant, with only 546 of the 1911 respondents aged ≥ 65 years not fully following COVID-19 health orders (28.6%).

We also advanced our understanding of why people were not or could not comply with health orders. Our results suggest reasons for noncompliance were nuanced and varied. The predominant reason given for not being able to follow social distancing and self-isolation orders was not being able to afford to miss work. Of the respondents who were not isolating as much as recommended, more than half listed work as the reason. Some participants indicated they were essential service workers or health care professionals; however, others working in nonessential industries also reported that work obligations and conditions prevented them from social distancing and self-isolating more. Future public health communications encouraging compliance with existing health guidance should be targeted not only at individuals but also at employers on how to minimize COVID-19 exposure, prevent viral spread in the workplace, and protect individuals working during the pandemic.

Age-related differences in noncompliance reflect how each group experienced the pandemic, and these differences can inform future health communication strategies to enhance compliance to public health orders. We describe key health communication strategies by age group in Table 3. People in the youngest age group (18-31 years) were the most likely to say they could not fully comply with health guidance because they did not have sufficient space to self-isolate (293/2905, 10.1%). Given the prevalence of shared residences (eg, college dorms, apartments) among young adults, this could be addressed through community-specific health messaging that provides guidance on how to minimize COVID-19 spread within shared living spaces. The youngest age group was also the most likely to be noncompliant because of the detrimental impact of self-isolation and social distancing on their mental and physical health. In discussing their experience with the pandemic, they were highly negative, expressing significantly more anxiety and using less positive emotion terms relative to the other age groups, and focused on the process of adjusting to limited social interactions. Together with results from the COVID Response Tracking Study that the majority of young Americans aged 18-34 years are experiencing poor mental health [20], these findings underscore the need for health communications targeting this age group to be responsive to the emotional impact of the pandemic on their lives. Future interventions should publicize information on available mental health resources and provide guidance on how to take care of mental health needs while complying with health orders.

People in the middle-aged groups were predominantly noncompliant because they could not afford to miss work. This age group was unique in that they were primarily focused on family. When they described the impact of the pandemic on their lives, they used the most first-person plural pronouns (ie, we, us), suggesting a group-oriented (as opposed to self-focused) mindset, and were the most likely to use language related to family. In addition, they focused on the impact of the pandemic on work and school closures for their family. Almost all of the individuals who cited children and childcare as a reason for noncompliance with health orders were in this age group. As more research emerges on the challenges of parenting and caring for others during the pandemic, health communications targeting these age groups should discuss strategies to maintain social distance while caring for children and family members. In addition, such messages should remind those who are caring for others to take care of themselves.

Table 3. Health communication strategies for COVID-19 messaging by age group.

| Age group | Experience of the pandemic | Noncompliance reasons | Individual-level messaging recommendations | Institution-level messaging recommendations |
|-------------|---|--|---|--|
| 18-31 years | <ul style="list-style-type: none"> Highest in anxiety and lowest in positive emotion terms Most focused on themselves | <ul style="list-style-type: none"> Most likely to cite mental health toll Most likely to cite need to work and to attend school Most likely to cite not having sufficient space to self-isolate | <ul style="list-style-type: none"> Address negativity by focusing on positive future outlook Emphasize the consequences of their virus-related behaviors on other people Publicize information about available mental health resources and share advice on how to take care of one's mental health needs while complying with health orders Discuss how to stay safe while at work (eg, wear masks during breaks), at school (eg, sanitize books and computers), or while exercising (eg, maintaining social distancing while running) Provide guidance on minimizing COVID-19 spread within a shared living space (ie, college dorms, apartments) | <ul style="list-style-type: none"> Provide guidance on minimizing COVID-19 spread within a shared living space (ie, college dormitories, apartments) Discuss how to stay safe while at work (eg, wear masks during breaks), at school (eg, sanitize books and computers), or while exercising (eg, maintaining social distancing while running, prioritizing outdoors exercise) Institutions should clearly communicate the importance of prevention measures for both personal and collective health |
| 32-64 years | <ul style="list-style-type: none"> Most focused on others Highly focused on family | <ul style="list-style-type: none"> Most likely to cite childcare as reason for noncompliance | <ul style="list-style-type: none"> Remind those caring for others to care for themselves | <ul style="list-style-type: none"> Provide strategies for how to safely social distance while caring for kids or other family members |
| ≥65 years | <ul style="list-style-type: none"> Most focused on health-related terms Lowest in anxiety and highest in positive emotion terms | <ul style="list-style-type: none"> Most likely to say they're already taking sufficient precautions | <ul style="list-style-type: none"> Recognize efforts and precautions already being taken by older populations Discuss symptomatology of the virus and provide clear instructions for accessing health services Provide information and resources to improve quality of life in isolation | <ul style="list-style-type: none"> Discuss strategies for how to safely social distance while caring for kids or other family member Discuss symptomatology of the virus and provide clear instructions for accessing health services Provide information and resources to improve quality of life in isolation |

It is perhaps not surprising that the oldest age group was the most likely to say they were complying as much as possible with health guidelines (1365/1911, 71.4%) given their elevated risk to the virus. In addition to focusing on their high-risk status in discussing the impact of the pandemic on their lives, they were also most likely to use health terms relating to sickness and symptoms. Surprisingly, however, they appeared to be resilient to the negative emotional effects of COVID-19—using the fewest number of words relating to anxiety and the most words relating to positive emotion to describe the impact of the pandemic on their lives. These results support suggestions made by others that, despite COVID-19 presenting a great deal of health risk to older adults, older adults possess life experience, perspectives, and contexts that can help them be emotionally positive and resilient in the face of the pandemic [21,22]. As the pandemic continues, health communications should be cognizant of the precautions already taken by older populations to keep themselves safe and recognize their ongoing efforts; rather than focusing on telling them to do things that most are already doing diligently, messaging should provide guidance on how to improve their quality of life while they continue self-isolation.

The increased emotional positivity and reduced self-focus in the language of older adults relative to younger adults has been documented in prior work examining large corpora of natural language generated by individuals across the lifespan in a diversity of contexts [23]. Given the elevated risk to older adults posed by COVID-19, one might expect the patterns of greater emotional positivity and reduced self-focus to disappear. Instead, we find that when asking specifically about the impact of the coronavirus crisis, the language of older adults still tends to be more emotionally positive and less self-focused than that of younger individuals. Consistent with other recent work [21], these results provide evidence that older adults' emotional positivity and reduced self-focus is robust even in the face of a significant threat.

While the general pattern of older individuals being more positive than younger individuals holds in the context of the pandemic, this positivity bias may be attenuated. We used data from two prior large-scale studies of natural language [23,24] to explore the extent to which the size of the gap in positive language usage between old and young adults observed in our data was comparable in size to gaps in non-COVID-19-related

language (see [Multimedia Appendix 1](#) for details on these comparisons). We found that the emotional positivity bias during COVID-19 was significantly smaller in magnitude than that bias observed in non-COVID-19 language (about 3 times smaller than the bias in Pennebaker and Stone [23] and 1.2 times smaller than the bias in Schwartz et al [24]). Furthermore, the difference we observed in anxiety-related words between older and younger adults (with younger people displaying significantly greater anxiety) was significantly larger in magnitude than in the non-COVID-19 language from prior works (about 7.8 times larger than the bias in Schwartz et al [24]). These exploratory comparisons suggest that the pandemic is exerting strong influences on different age groups' emotions, which are being reflected in their language. The well-documented positivity bias in the emotions of older adults was observed here, but the size of that bias shrank during COVID-19, possibly because the pandemic poses a significant new threat to the health of older individuals.

Of the seniors who said they were not fully compliant with social distancing and self-isolation measures (546/1911, 28.6%), they were most likely to say this was because they could not afford to miss work (146/546, 26.7%) or because they felt like they were taking sufficient other precautions outside of the health guidance (ie, frequent hand washing, generally avoiding people but not social distancing or isolating) (119/546, 21.8%). In response to the latter issue, health messaging should provide clear, consistent reminders about what constitutes sufficient "compliance" with COVID-19 prevention measures, particularly as health orders change throughout the pandemic.

The ability to rapidly assess public sentiment through natural language processing can facilitate informed policy decision making during a pandemic. Natural language processing methods such as LIWC and the meaning extraction method allow researchers, policymakers, and government officials to "take the pulse" of their citizens, to see how they are experiencing the impact of the pandemic, and to know why they are or are not complying with public health orders. Such insights may help legislators and health strategists pivot their messaging to be more responsive to the needs of the public and tailored to the challenges facing specific communities.

Limitations

There are several limitations to our research. First, our use of an online convenience sample and recruitment via social media may have potentially influenced the characteristics of our sample [25]. Of note, our sample is especially highly educated and comprised more White individuals relative to the broader United States population. Future work on age-related differences in COVID-19 experiences and noncompliance should involve nationally representative data and lifespan sampling to have a more representative sample from which conclusions can be more generalizable. It is worth noting, however, that our finding that older individuals are emotionally positive in the face of COVID-19 is corroborated by recent findings collected from a nationally representative sample [21]. In addition, we may observe some degree of social desirability in our responses

given that we are asking about a socially charged issue. While we did observe a relatively high rate of noncompliance in our study, it may be that additional people who were noncompliant were not willing to admit it. Furthermore, we may see biases in the reasons participants give for their noncompliance, such that participants may be less willing to report that they are failing to fully comply with health orders because of reasons that are socially undesirable, such as wanting to go to social engagements.

Our timing of data collection early in the COVID-19 outbreak in the United States may mean that participants' experiences look different now than they did earlier given the rapidly changing nature of the pandemic. Continuous assessment of public sentiment and responses to health guidance is necessary to understand current experiences as the circumstances of the pandemic change over time. Finally, regarding our public health messaging recommendations, while age is a key demographic characteristic upon which health communication messages can be tailored, personalization of communications using multiple demographic and behavioral characteristics has been found most effective in inciting behavior change [26]. Policymakers and other communicators should consider multiple characteristics when designing messages around COVID-19 (eg, age, gender, socioeconomic status, health status).

Conclusions

Our findings suggest that there are meaningful differences in how people of different ages experience COVID-19 and respond to health measures to prevent its spread, such as social distancing. Notably, younger people (18-31 years) discussed the impact of COVID-19 with more self-focused and negative emotional language, middle-aged people were more other-focused (32-44 years) and concerned with family (32-64 years), and older people (≥ 65 years) were more concerned with health-related terms but were also lower in anxiety. Despite the threat posed to older people by COVID-19, they were more emotionally positive than young people in their language use. However, we present evidence that the magnitude of this positivity bias may be attenuated by the pandemic. A closer examination of noncompliance with COVID-19 prevention measures also revealed age-related differences. Although the most common reason for noncompliance across age groups was not being able to afford missing work, younger people reported difficulty finding space to isolate due to shared living arrangements and managing their mental and physical health, middle-aged people reported childcare obligations, and older people perceived themselves as able to take sufficient precautions. Health communication messages attempting to increase compliance with necessary health measures may be strengthened by focusing on and addressing the individual- and institutional-level reasons for noncompliance within particular age groups. The results from our natural language processing analysis of open-ended survey questions demonstrate how researchers and policymakers can rapidly ascertain how their communities are feeling and responding to COVID-19 amid changing conditions.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Supplementary materials.

[[DOCX File, 32 KB - humanfactors_v8i2e26043_app1.docx](#)]

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Abbreviations

LIWC: Linguistic Inquiry and Word Count

RQ: research question

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Original Paper

Older Patients' Competence, Preferences, and Attitudes Toward Digital Technology Use: Explorative Study

Rikke Terp¹, MHSc; Lars Kayser², MD, PhD; Tove Lindhardt¹, MScN, PhD

¹Department of Internal Medicine, Herlev and Gentofte Hospital, Copenhagen University Hospital, Hellerup, Denmark

²Department of Public Health, University of Copenhagen, Copenhagen, Denmark

Corresponding Author:

Rikke Terp, MHSc
Department of Internal Medicine
Herlev and Gentofte Hospital
Copenhagen University Hospital
Hospitalsvej 4
Hellerup, 2900
Denmark
Phone: 45 26823909
Email: rikke.terp@regionh.dk

Abstract

Background: Malnutrition is prevalent in older patients, which is associated with severe consequences such as a decline in functional status, increased risk of readmission, and increased mortality. A tablet-based eHealth solution (Food'n'Go) was recently developed and introduced at our clinic to support older patients' involvement in nutritional interventions during their hospitalization, thereby enhancing their awareness and motivation for choosing the right food to obtain sufficient calorie and protein intake. To reap the full benefits from the eHealth solution, the technology should be introduced and accompanied by support that targets the end users' competence level and needs.

Objective: In this study, we aimed to explore older patients' readiness (ie, competence, preferences, and attitudes) toward the use of information and communication technology (ICT), and to identify the factors that may act as barriers or facilitators for their engagement with health technology.

Methods: A descriptive and explorative study was performed using triangulation of data derived from semistructured interviews and questionnaires (based on the Readiness and Enablement Index for Health Technology [READHY] instrument). Older hospitalized patients (age ≥ 65 years; N=25) were included from two hospitals in Denmark.

Results: The majority (16/25, 64%) of the older patients (median age 81 years) were users of ICT. The qualitative findings revealed that their experiences of benefits related to the use of ICT facilitated usage. Barriers for use of ICT were health-related challenges, limited digital literacy, and low self-efficacy related to ICT use due to age-related prejudices by their relatives and themselves. The qualitative findings were also reflected in the low median scores on the eHealth Literacy Questionnaire (eHLQ) READHY scales within dimensions addressing the user's knowledge and skills (eHLQ1: 1.8; eHLQ3: 2.0), and the user experience (eHLQ6: 2.0; eHLQ7: 1.5).

Conclusions: Older patients are potential users of ICT, but experience a variety of barriers for using eHealth. When introducing older patients to eHealth, it is important to emphasize the possible benefits, and to offer support targeting their knowledge, skills, and motivation.

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KEYWORDS

eHealth literacy; eHealth; self-management; older patients; explorative study

Introduction

Malnutrition is a prevalent and challenging area in health care for older patients [1-3] with severe consequences such as

decreased physical function [1], prolonged hospitalization [4], readmissions [5], and mortality [1,4,6]. Multiple interventions targeting the prevention of malnutrition in older patients have been investigated, and the majority consist of dietary

interventions with varying effects [7-9]. To support older patients in eating adequately, interventions that address the individual's motivation and preferences are required [10]. Hence, patient involvement is a prerequisite, and eHealth technology may be a useful tool in this regard. However, few technology studies have focused on the management of malnutrition, and only a limited number of such studies have included older patients. It is commonly considered that older patients do not utilize and benefit from digital technologies [11-13]. Due to this faulty assumption, older people are given less opportunities to use eHealth [13,14]. Indeed, former studies have described a positive attitude among older patients toward digital technologies [15-18], but that they may have less experience with these tools than younger people [19]. These results are supported by data from Statistics Denmark, which show a steady increase in the use of digital technologies among older age groups; in 2019, 85% of people aged 75 to 89 years used internet banking compared to only 61% in 2011 [20]. Former studies have investigated the specific barriers for older patients to use digital technologies [11,16,17,21], identifying lack of digital literacy, knowledge, and confidence in using technology as predominant barriers. However, this is a new and expanding research area and the evidence remains limited. Moreover, an understanding of older patients' capacity to engage with digital technologies requires insight into their knowledge, skills, and perception of the technology (ie, eHealth literacy) [22], taking the social context into consideration [23]. Recently the Readiness and Enablement Index for Health Technology (READHY) instrument was developed, which can capture not only individuals' eHealth literacy but also the social context, and their ability to manage the burden of treatment and illness [24].

In a recent project implemented at two hospitals in the Copenhagen area, our research group, in collaboration with the information technology company Movesca, developed a new eHealth solution (Food'n'Go) with the aim of supporting older

patients (>65 years) to participate in nutritional interventions while hospitalized, thereby enhancing their awareness and motivation for eating sufficiently [25]. Food'n'Go is an app provided on a computer tablet where the patients can (1) access a menu of food choices, (2) order meals, (3) register food intake, and (4) receive feedback. To reap the full benefits from such an eHealth solution, it should be introduced and accompanied by support targeted to the end user's competence and needs. Therefore, as an adjunct study to the above technology study, we are developing an educative intervention supporting older patients in their use of this eHealth tool to increase the adoption and advantages of using the technology. Development of such an educative intervention requires not only knowledge of the end user's competencies, needs, and abilities to participate in the nutritional interventions but also to address the readiness for usage of technology.

Toward this end, the aim of this study was to explore older patients' competencies, preferences, and attitudes toward use of information and communication technology (ICT), and to gain an understanding of the barriers and facilitators for their motivation to engage with eHealth.

Methods

Design

The overall design has been reported elsewhere [26]. Briefly, this report builds on field studies that addressed older patients' competencies, preferences, and attitudes toward food and technology. The focus on nutrition and food has been reported previously [26]. We here report our findings in relation to the technology perspective. In short, we recapture the principles of the study design to establish the context for the results, analysis, and discussion. This study applied a descriptive and explorative design using data triangulation. Table 1 illustrates the methodology for inclusion, recruitment, data collection, and analysis.

Table 1. Description of participant recruitment, inclusion and exclusion criteria, data collection, and data analysis.

| Stage of the study | Description |
|--|---|
| Recruitment: consecutive sampling | |
| Inclusion criteria | Age ≥ 65 years (N=25) Admitted at one of the two selected hospital units specialized in internal medicine: Hospital A (n=12) and Hospital B (n=13) |
| Exclusion criteria | Total excluded N=60 Already included (n=6, 10%), unwilling to participate (n=12, 20%), terminal illness (n=2, 3%), discharged before inclusion (n=13, 22%), unable to provide informed consent (n=27, 45%) |
| Data collection | |
| Time period | March 2017 to July 2017 ^a |
| Interviews | Individual semistructured interviews, interview guided by READHY ^b dimensions |
| Data analysis | |
| Qualitative data | Content analysis; coded with an inductive approach using the management software program NVivo 11 |
| Quantitative data | |
| Descriptive statistics | READHY scores, participant characteristics |
| Test statistics | χ^2 (categorical variables), Mann-Whitney <i>U</i> test (continuous variables); <i>P</i> <.05 indicated significance analyzed with SPSS version 25 |

^aExcept for two male participants who were included in March 2018 due to overrepresentation of women.

^bREADHY: Readiness and Enablement Index for Health Technology.

Participants and Procedure

The participants (25 hospitalized patients) were recruited from two units specialized in internal medicine from two hospitals under the same administration in Denmark. To capture as much variation as possible in competencies, preferences, and attitudes toward ICT in the group of older patients, we consecutively included the participants using a cross-sectional sampling strategy. On randomly selected days, patients fulfilling the inclusion criteria were included. To ensure heterogeneity in terms of socioeconomic status, we purposefully included participants from two different hospital units. The two hospitals (Hospital A and Hospital B) serve different populations regarding socioeconomic status. People living in the uptake area of Hospital B have a lower socioeconomic status compared to those in the uptake area of Hospital A. In Table 1, we describe eligible patients and reasons for nonparticipation.

Data Collection and Analysis

The data included both qualitative and quantitative data from semistructured interviews and the READHY questionnaire. The 25 participants were asked to fill in the READHY questionnaire, followed by individual interviews with the first author (RT). The interviews were performed at the hospital to gain an understanding of the experiences, competencies, and attitudes of older patients toward the use of ICT and their management of nutritional needs. An interview guide based on the dimensions from the READHY tool was developed and used. The first author undertook the data collection. We planned to include 10-12 participants from each hospital unit and to evaluate whether categories of participants scoring high and low in the READHY themes of self-management, social support, and eHealth literacy were represented, and that saturation with

respect to new aspects of ICT usage or understanding of nutrition was achieved. For Hospital B, we lacked some male representatives and therefore included a total of 13 participants from this hospital.

Qualitative content analysis was used [27,28]. To ensure trustworthiness, the analysis and interpretation of the qualitative data were carried out as follows. The coding of the first three transcribed interviews was reviewed and discussed with all authors. The transverse analysis and interpretation were performed in collaboration between two authors (RT and TL) and were discussed with the other author (LK) until consensus was reached. The interviews were conducted, transcribed, and analyzed in Danish. Quotations included herein were translated into English by a bilingual translator in collaboration with RT to ensure the meaning was not distorted.

Theoretical Framework

As previously reported, we used the READHY instrument as a theoretical framework to explore the informants' capacity to utilize an eHealth solution. READHY is a psychometrically validated instrument developed to measure an individual's health technology readiness [24]. It consists of 65 items covering 13 dimensions from three distinct instruments measuring the concepts of eHealth literacy, health literacy, and self-management. The READHY instrument is based on the concepts of eHealth literacy comprising the seven dimensions from the eHealth Literacy Questionnaire (eHLQ) [29], which address: (1) the user's knowledge and skills (eHLQ1, eHLQ2, and eHLQ3); (2) the user experience (eHLQ6 and eHLQ7); (3) the users' trust toward digital technology (eHLQ4); and (4) the user's motivation for engaging with the technology (eHLQ5). It has been argued that an individual's capability to utilize eHealth is influenced by their competence in managing the

burden of treatment and illness, as well as the social context such as social support [23,24]. READHY addresses social aspects such as support from relatives and health care professionals in two dimensions from the Health Literacy Questionnaire (HLQ; HLQ1 and HLQ4) [30]. Additionally, READHY contains four dimensions from the Health Education Impact Questionnaire (heiQ) [31], which addresses perspectives of self-management: self-monitoring and insight into their own health (heiQ3), constructive attitudes and approaches (heiQ4), skill and technique (heiQ5), and emotional distress (heiQ8). The 13 distinct dimensions captured in the READHY instrument are measured on a Likert scale with the following response categories: 1, strongly disagree; 2, disagree; 3, agree; and 4, strongly agree. Within each dimension, the items sum up to a composite score: 1 is the least desirable score and 4 is the most desirable score.

Ethical Considerations

Mandated by the Danish Data Protection Agency, the study was approved by the Capital Region of Denmark (local record number HGH-2017-021). The Regional Ethical Committee (j.nr H-17006045) evaluated the study and found that ethical approval was not required. Verbal and written information about the study were provided to all participants by RT and they signed an informed consent form.

Results

Patient Characteristics

A total of 25 out of 85 eligible patients were included in this study. The median age was 81 years and 13 (52%) of the patients were women. Further patient characteristics are summarized in Table 2. The results in Table 2, except for those related to digital use, were previously reported [26].

Table 2. Participant characteristics.

| Variables | Total sample (N=25) | Hospital A (n=12) | Hospital B (n=13) | <i>P</i> value ^a |
|--|---------------------|-------------------|-------------------|-----------------------------|
| Age (years), median (IQR) | 81 (72-88) | 82 (73-90) | 81 (70-88) | .55 |
| Sex (female), n (%) | 13 (52) | 5 (42) | 8 (62) | .32 |
| Civil status; living alone, n (%) | 13 (52) | 6 (50) | 7 (54) | .85 |
| Digital use; use of ICT ^b , n (%) | 16 (64) | 9 (75) | 7 (54) | .27 |
| School level, n (%) | | | | .40 |
| ≤7 years | 8 (32) | 2 (17) | 6 (46) | |
| 8-9 years | 6 (24) | 3 (25) | 3 (23) | |
| 10-11 years | 9 (36) | 6 (50) | 3 (23) | |
| Upper Secondary School Leaving Examination | 2 (8) | 1 (8) | 1 (7) | |
| Education level, n (%) | | | | .25 |
| Comprehensive ^c | 6 (24) | 2 (17) | 4 (31) | |
| Short education ^d | 11 (44) | 4 (33) | 7 (54) | |
| Medium education ^e | 6 (24) | 4 (33) | 2 (16) | |
| Long education ^f | 2 (8) | 2 (17) | 0 (0) | |

^aPearson χ^2 test was used for categorical variables and Mann-Whitney *U* test was used for continuous variables.

^bICT: information and communication technology.

^cCorresponding to International Standard Classification of Education-2011 levels 1 and 2.

^dCorresponding to International Standard Classification of Education-2011 levels 3, 4, and 5.

^eCorresponding to International Standard Classification of Education-2011 level 6.

^fCorresponding to International Standard Classification of Education-2011 levels 7 and 8.

Quantitative Analysis

The informants were interviewed on the third day after admission. No significant differences in informants' characteristics between Hospital A and Hospital B were found. The informants' scores from the READHY instrument are summarized in Table 3. The informants from Hospital A had a

higher score on 11 out of 13 scales. However, only significantly higher scores were found for two scales: "Self-monitoring and insight" and "Feeling understood and supported by health care providers." Informants who used ICT had a significantly higher score than nonusers on 5 out of 7 scales within the eHealth literacy dimensions (Table 4).

Table 3. Readiness and Enablement Index for Health Technology (READY) scores for the total sample and between patients from the two hospitals.

| READY dimensions ^a | Total sample (N=25), median (range) | Hospital A (n=12), median (range) | Hospital B (n=13), median (range) | P value ^b |
|---|--|--------------------------------------|--------------------------------------|----------------------|
| heiQ^c | | | | |
| heiQ3: self-monitoring and insight | 2.8 (2.0-4.0) | 3.2 (2.0-4.0) | 2.7 (2.2-3.2) | .007 |
| heiQ4: constructive attitudes and approaches | 3.2 (1.0-3.8) | 3.2 (2.5-3.8) | 3.2 (1.0-3.8) | .44 |
| heiQ5: skills and technique acquisition | 3.0 (1.3-4.0) | 3.0 (2.0-3.8) | 2.8 (1.3-4.0) | .35 |
| heiQ8: emotional distress ^d | 2.5 (1.2-3.5) | 2.6 (1.2-3.5) | 2.5 (1.8-3.5) | .51 |
| HLQ^e | | | | |
| HLQ1: feeling understood and supported by health care providers | 3.0 (1.0-4.0) | 3.8 (2.0-4.0) | 2.8 (1.0-4.0) | .004 |
| HLQ4: social support for health | 3.4 (1.0-4.0) | 3.8 (2.2-4.0) | 3.0 (1.0-4.0) | .14 |
| eHLQ^f | | | | |
| eHLQ1: ability to process information | 1.8 (1.0-4.0) | 1.9 (1.0-3.2) | 1.8 (1.0-4.0) | .76 |
| eHLQ2: understanding of health concepts and language | 2.8 (1.0-3.6) | 3.0 (2.4-3.6) | 2.6 (1.0-3.6) | .054 |
| eHLQ3: ability to actively engage with digital services | 2.0 (1.0-3.4) | 1.9 (1.0-3.2) | 2.2 (1.0-3.4) | .79 |
| eHLQ4: feel safe and in control | 3.0 (1.8-4.0) | 3.0 (2.2-4.0) | 2.8 (1.8-3.2) | .07 |
| eHLQ5: motivated to engage with digital services | 2.4 (1.0-3.6) | 2.5 (1.0-3.0) | 1.8 (1.0-3.6) | .25 |
| eHLQ6: access to digital services that work | 2.0 (1.0-3.0) | 2.5 (1.0-3.0) | 2.0 (1.3-2.8) | .78 |
| eHLQ7: digital services that suit individual needs | 1.5 (1.0-3.3) | 1.6 (1.0-3.3) | 1.5 (1.0-3.0) | .68 |

^aThe dimension scores are based on following response categories: 1, strongly disagree; 2, disagree; 3, agree; and 4, strongly agree. A high score is a more desirable trait. The heiQ3, heiQ4, heiQ5, heiQ8, HLQ1, HLQ4, and eHLQ2 scores have been reported previously [26].

^bMann-Whitney *U* test.

^cheiQ: Health Education Impact Questionnaire.

^dReverse score; a high score means a low level of distress.

^eHLQ: Health Literacy Questionnaire.

^feHLQ: eHealth Literacy Questionnaire.

Table 4. Readiness and Enablement Index for Health Technology (READHY) scores for information and communications technology (ICT) users versus nonusers.

| READHY dimensions ^a | ICT users (n=16), median (range) | ICT nonusers (n=9), median (range) | P value ^b |
|---|----------------------------------|------------------------------------|----------------------|
| heiQ^c | | | |
| heiQ3: self-monitoring and insight | 2.9 (2.0-3.7) | 2.8 (2.2-4.0) | .95 |
| heiQ4: constructive attitudes and approaches | 3.0 (1.0-3.8) | 3.2 (2.6-3.8) | .33 |
| heiQ5: skills and technique acquisition | 3.0 (1.3-4.0) | 3.0 (2.0-3.8) | .49 |
| heiQ8: emotional distress ^d | 2.5 (1.2-3.3) | 3.2 (1.8-3.5) | .20 |
| HLQ^e | | | |
| HLQ1: feeling understood and supported by health care providers | 3.3 (1.0-4.0) | 3.0 (1.8-4.0) | .84 |
| HLQ4: social support for health | 3.1 (1.0-4.0) | 3.6 (2.4-4.0) | .30 |
| eHLQ^f | | | |
| eHLQ1: ability to process information | 2.4 (1.0-4.0) | 1.2 (1.0-1.8) | .004 |
| eHLQ2: understanding of health concepts and language | 2.8 (1.0-3.4) | 3.0 (2.2-3.6) | .09 |
| eHLQ3: ability to actively engage with digital services | 2.5 (1.0-3.4) | 1.4 (1.0-1.6) | <.001 |
| eHLQ4: feel safe and in control | 2.9 (1.8-3.6) | 3.0 (2.0-4.0) | .69 |
| eHLQ5: motivated to engage with digital services | 2.7 (1.0-3.6) | 1.8 (1.0-2.4) | .02 |
| eHLQ6: access to digital services that work | 2.7 (1.0-3.0) | 1.5 (1.3-2.0) | .02 |
| eHLQ7: digital services that suit individual needs | 2.0 (1.0-3.3) | 1.0 (1.0-2.0) | .01 |

^aThe dimension scores are based on following response categories: 1, strongly disagree; 2, disagree; 3, agree; and 4, strongly agree. A high score is a more desirable trait. The heiQ3, heiQ4, heiQ5, heiQ8, HLQ1, HLQ4, and eHLQ2 scores have been reported previously [26].

^bMann-Whitney *U* test.

^cheiQ: Health Education Impact Questionnaire.

^dReverse score; a high score means a low level of distress.

^eHLQ: Health Literacy Questionnaire.

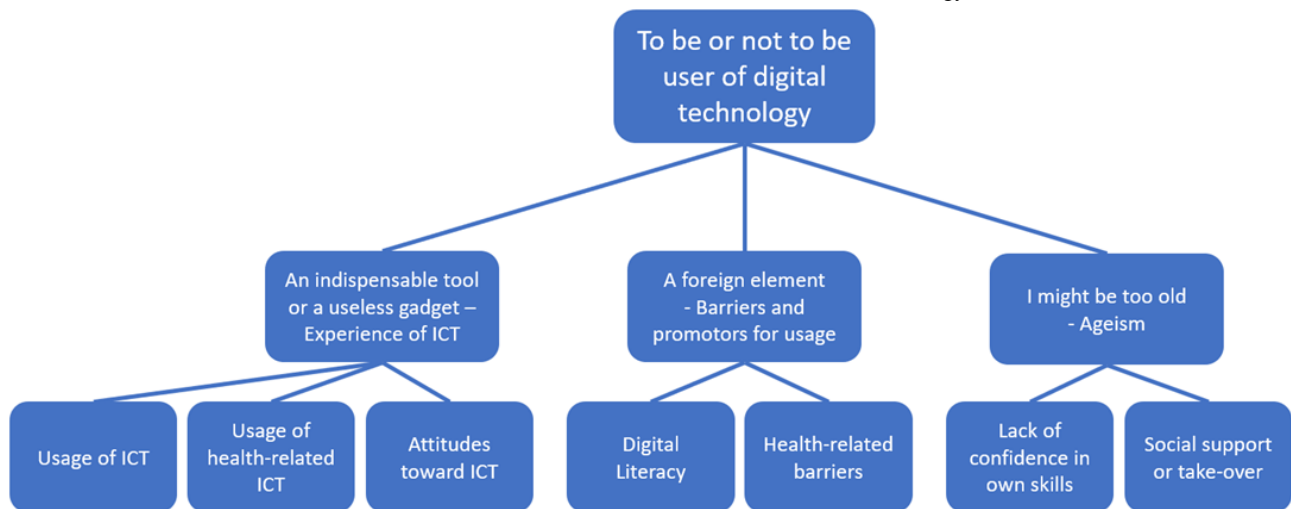
^feHLQ: eHealth Literacy Questionnaire.

Qualitative Analysis

Main Themes

From the qualitative analysis, one main theme emerged: To be or not to be a user of technology. There were three subthemes identified: (1) An indispensable tool or a useless gadget:

experiences of ICT; (2) A foreign element: barriers and promoters for usage; and (3) I might be too old: ageism (Figure 1). The qualitative findings showed a noteworthy diversity in the informants' attitude, use, and experience with ICT. The findings revealed how the use and nonuse of ICT was related to the informants' expectations of derived benefits and their own competence.

Figure 1. Main theme, subthemes, and subordinate themes. ICT: information and communication technology

An Indispensable Tool or a Useless Gadget: Experience of ICT

Theme Overview

This theme covers the diversity of the informants in their experiences and attitudes toward ICT. The informants' experiences of ICT spread over a spectrum. One side of the spectrum included patients that used ICT on a daily basis and experienced it as an indispensable tool in their lives. The other side of the spectrum included informants who never used ICT and regarded it as irrelevant; some found it intimidating and some even considered it to be a threat to their usual way of living. In general, the nonuse of ICT was not a sign of rejection by the informants, but rather an expression of them feeling that they were not a target group for this technology.

Usage of ICT

Most of the informants used ICT at home on a daily basis, and several had various computer devices, including a personal computer, tablet, and smartphone. They used ICT for different purposes such as information seeking, communication with friends and family via email, managing finances, and entertainment. Use of social media such as Facebook was also mentioned. Notably, many of the nonusers of ICT had been introduced to ICT earlier in life, such as through personal computer training in the local residents club or seniors club. However, the skills acquired at such training events had been forgotten, despite their initial interest:

I am member of a senior citizens club through HK (a trade union)...Yes, it is more than 10 years ago we got the chance to try a computer, and it was quite exciting. [Informant A; 87 years]

When asked directly, the informant could not explain why she was not using ICT currently, except that she was managing just fine without it. The informants most frequently explained their nonuse of ICT as lack of need or interest. When asked if they would like to learn to use ICT, one informant responded:

Well, um, in a way, yes, but on the other hand: what would I use it for?" [Informant B; 81 years]

Usage of Health-Related ICT

Use of ICT in relation to health and well-being was common, primarily to look up health information. The search engine Google was used by many, but others also mentioned the national health portal (sundhed.dk), which after logging in with a national personal identifier provides access to various health services, including the electronic health record, prescribed drugs, and paraclinical data. This portal also provides information about health services and resources, and on different conditions and how they are treated using a so-called patient "handbook" without needing to log in. The informants were mainly searching for information on diseases, treatments, and medicine. Beyond information seeking, some informants mentioned how they used digital services of their general practitioners (GPs) for booking appointments or renewal of drug prescriptions. The informants also used access to their electronic health record for information about their treatment. In general, the informants had limited experience with using ICT for monitoring their health conditions. One exception was a patient who used an app on his smartphone for monitoring physical activity (ie, the distance moved in a day). This informant differed from the others as he was younger. Health-related use of ICT was mainly focused on treatment and prevention of complications of an existing disease and, to a limited extent, on health promotion.

Daily use of ICT did not always encompass purposes related to health and well-being. For instance, several informants explained that they did not take advantage of the digital health services offered by the GP. This was not due to worries about digital safety. In general, ICT users trusted the security in the digital systems when sharing their data, and data security did not seem to be a concern among nonusers. For some informants, the use of health-related ICT was perceived as a risk of being a substitute for personal contact with the health care professionals (eg, their GP). Several informants explained how the information was generally better and more easily understood when received in person, and some expressed concerns about misunderstandings. Other reasons mentioned for not using ICT for health-related purposes was lack of knowledge, user competence, and interest. The latter was often an expression of

lack of knowledge of the opportunities made available by the technology.

Attitudes Toward ICT

In general, the ICT users had a positive attitude toward ICT. Their narratives revealed how their attitudes were associated with their experiences of various ICT benefits in their everyday lives. Access to all kinds of information on the internet was especially appreciated:

I basically find a computer an indispensable tool. If you want to know something, well, ask the computer.
[Informant C; 91 years]

Some informants expressed how ICT helped them manage the challenges of living with a chronic condition, such as by providing information about illness and treatment. Easy access to information on the internet helped prepare them for more qualified conversations with health care professionals:

...It probably means that you are better prepared for at least some of the doctor's consultations...I mean, in reality, it is all about asking the right questions.
[Informant D; 73 years]

Other informants described how using the GP's digital services made appointment booking and renewing prescriptions easier, and therefore making interactions less dependent on the GP's telephone hours. The analysis further revealed examples as to how ICT had a positive influence on compliance with medication, such as the timely ordering of medication by digital renewal of prescriptions and correct administration of medication due to easy access to information.

Not all informants considered ICT to be an indispensable tool. In general, the nonusers lacked interest in using ICT, as they did not consider it relevant. A negative attitude was not common, but was observed. One informant rejected digital communication from public authorities but still used ICT for email with friends and family.

But now, when you are being pushed, I feel genuinely annoyed over...um...digital pressure from society, from the municipalities. I feel it isn't right (...) I have applied to be, what do they call it, not-digitalized, and I got approved [Informant E; 88 years]

ICT was experienced as something new and unfamiliar, influencing their attitudes toward using it. For some, this attitude was a barrier for using ICT, whereas others embraced this challenge and embarked on learning new skills to overcome the difficulties.

I want to learn, he (son) shouldn't tell me what to do, he should be teaching me how to, so I can do it myself; otherwise I will have a gigantic problem on my hands as soon as he is out of the door [Informant F; 76 years]

Despite the challenges experienced, these were not always a hindrance to using the technology. Generally, the informants accepted the occasional challenges and the fact that they sometimes needed assistance with completing the task they were engaged in. Technical challenges such as an inaccessible system or difficulties operating the system were met with

patience and confidence. An acceptance attitude was apparent, acknowledging that things may take time and it was sometimes a matter of waiting, either for the system to work again or for the necessary support to be available.

But sometimes it's a real mess (laughing).

RT: What is it that's a mess?

It's all of it, isn't it? I mean, (...) then I wait a bit, then I try again (...) then it usually ends up working
[Informant G; 70 years]

It became apparent in the informants' narratives that the nonuse of ICT could not necessarily be explained by being technology-averse in general, as some of the nonusers handled other technological devices without problems, such as for monitoring their blood sugar.

A Foreign Element: Barriers and Promotors for Usage

Theme Overview

Personal attributes such as health-related challenges and limited digital literacy among the informants were barriers for their use of ICT. The informants generally indicated an acceptance of the barriers experienced, and they acknowledged that they often depend on support that is mainly provided by their children.

Digital Literacy

A consistent theme was that the informants felt unfamiliar with the language and concepts of the digital systems and had a hard time understanding them. Some emphasized that this was not due to cognitive limitations, as they felt they had good linguistic skills, but rather to their introduction to ICT late in life:

It's not like I am linguistically challenged but there have been some instructions where I was thinking: what in the world are you talking about? [Informant H; 81 years]

The informants mentioned examples of how they encountered new words that made no sense to them, which complicated navigating the system. Age was often considered the prime reason for these linguistic challenges. The informants were older, and technology had entailed estranged procedures and language for which they had no prior experiences to cope with. Time was experienced as passing fast, particularly with regard to the digital age, introducing swift changes in functions as well as language and expressions in relation to technology.

Because when I was 18-20 years old, nobody said anything about digital files, we didn't say "stand-by" either, we said "stop." (...) there are so many new words and things in the systems, and you can't keep up, also because time passes so quickly for us
[Informant C; 91 years]

One informant used ICT to stay in touch with friends and family by email, but she found it challenging, as she sometimes forgot which button to press. This informant labeled herself as suffering from technological illiteracy.

Health-Related Barriers

Various health-related barriers such as arthritis in the fingers or reduced vision were described as making it difficult to operate

certain devices, including when using touchscreens on tablets and smartphones. Informants with impaired vision experienced the use of tablets and phones with small screens challenging. Many preferred the computer as it provides a larger screen. Previously, some of the nonusers had used a personal computer, but had experienced increasing problems over time, which they related to a decline in their cognitive skills such as difficulties with learning and memory. Thus, the informants experienced challenges making the use of both hardware and software either difficult or impossible. Mostly, the obstacles experienced using ICT were related to personal barriers and not to a lack of functionality of the ICT systems.

But then they introduced new systems, and I have a Windows10, which for me is more complicated. And so, I find it harder to learn now. (...) there is no doubt I am having a hard time figuring things out. This is also because I cannot see things properly. It is a terrible show-stopper that I cannot see properly. This is my biggest challenge. [Informant I; 93 years]

However, one informant attributed the challenges to the digital system. He was an experienced ICT user and differed from the other informants as he was younger:

You can say, they are different systems ... iPad and iPhone are different from PC, right? It doesn't always work well together. [Informant J; 69 years]

I Might Be Too Old: Ageism

Theme Overview

This theme describes an understanding that appeared to be common both among the informants and also the social network, indicating that increased age was associated with limited competence to benefit from ICT usage. This understanding seemed in itself to be a substantial barrier for not using ICT at all but also prevented ICT users from expanding their use to health-related purposes.

Lack of Confidence in Own Skills

A general lack of confidence in their own skills in ICT use among the informants was apparent throughout the data both among users and nonusers. This was often based on the attitude that age had the upper hand and made it increasingly difficult to use ICT. For some, however, this attitude was based on prejudice and not from real experience with ICT:

I am not so good at this sort of thing, and then I'd rather not do it at all (...) I keep telling myself I can't and then I'd rather not. [Informant K; 89 years]

Age was the dominant reason given by nonusers of ICT, combined with the assumption that the effort demanded to acquire the necessary skills was too great, and, in view of their remaining years, not worthwhile, particularly since many had no expectations for ICT to benefit them in their present situation and age. Even informants who actually used ICT lacked confidence in their possibilities in acquiring the necessary skills for using ICT for health-managing purposes.

I really don't have the capacity or skills for such stuff, no, I can't do that.

RT: But you are using that PC, aren't you?

Yes, but not for that sort of thing, I mostly use it for fun [Informant L; 92 years]

Apparently, the informants' relatives (eg, the children) also assumed that the older patients were not able to benefit from ICT and that the way they use it may cause malfunction of the technology due to their lack of skills.

"Stay away from that (the computer) (...) You don't understand it anyways," she says (the daughter)...She might be right! (...) But I'm told it's not so hard. Although my children say: "You don't need a mobile phone, you don't understand it, anyway." [Informant M; 91 years]

Social Support or Take-Over

The need for assistance with a variety of challenges that arose with using ICT was common. Generally, the informants experienced receiving the support they needed. Several described the various options for free technology support in their local resident community center or seniors club. Children and grandchildren were described as the main source of support, and very competent.

We have such great grandchildren who know much more than everybody else (laughs). That's when we get to learn, right? And then I have a son-in-law who is an IT expert. [Informant N; 85 years]

The informants expressed gratitude for the support from their children, but there were occasions where this support led to the children taking over instead. When asked if they would like to try the computer, one informant responded:

No (...) I'm just fine without. And if I needed help with anything, one of my children would do it for me. [Informant O; 79 years]

Some informants had previously been introduced to ICT but had either stopped using it or never really started. This lack of use was seemingly not out of rejection of ICT, but more a passive decision fueled by the lack of expectations from their surroundings and the lack of confidence progressing steadily with age.

Discussion

Principal Findings

The aim of this study was to explore older patients' competencies, preferences, and attitudes toward use of ICT, and to gain an understanding of both the barriers and facilitators for their motivation to engage with eHealth. Our findings contradict the perception that older patients cannot or will not use ICT. The qualitative and quantitative data revealed that older patients were indeed users of ICT, but their competence, ability, and preferences may differ from those of younger people. A main finding of this study was the large diversity in the informants' experiences with the use of ICT. This spanned from daily use to no use at all. The majority of the informants used ICT on a daily basis, which was in alignment with former studies [15,21,32] as well as with data from Statistics Denmark, showing that 51% of the 65-74 year olds and 26% of the 75-89

year olds use the internet on a daily basis [20]. Several informants had experiences with health-related ICT use. Information seeking was common, but they had limited experience with monitoring their own health through ICT. However, this study also revealed that some informants never used ICT and were not motivated to begin.

The wide range in the use of ICT was also reflected in the differing competencies among the informants, indicating differing needs for support to utilize eHealth. A predominant factor for the informants' user skills related to ICT was their age, as they had been introduced to it late in life. The qualitative data illustrated how many were not familiar with the "digital language," and some experienced this as a challenge to be overcome, while others saw it as a barrier preventing them from actual use of ICT. This qualitative finding was also reflected in the low READHY score on the scale within the dimension "Ability to process information" (eHLQ1), which covers the capability to read, apply, and understand context-specific language such as health and information technology [29]. In contrast, there was no difference in scores between users and nonusers of ICT on the scale within the eHealth literacy dimension "Understanding of health concepts and language" (eHLQ2), which covers the feeling of having knowledge of basic physiological functions and how to take care of one's own health [29]. Furthermore, we found no difference between the scores of users and nonusers on the scales within the four self-management dimensions (heiQ3, heiQ4, heiQ5, and heiQ8), which indicates that the nonusers' readiness to engage with ICT was limited by a low level of eHealth literacy rather than by their health-related self-management competence. In a hospital setting, it is expected that older patients with acute illness are even more challenged in their ability to obtain and understand information. This emphasizes the importance of providing older patients with support for computer skills and introducing technology in a language familiar to them.

The informants using ICT differed from the nonusers by having experience with the benefits of ICT. This experience of ICT as a useful tool for everyday tasks seemed to have a facilitating influence on ICT usage, which corresponds with several other studies [15,16,21,33]. Both de Veer et al [15] and Van Houwelingen et al [21] found that acceptance and use of ICT were influenced by trust in its derived benefits, also termed "performance expectancy" in technology acceptance theory. A prerequisite for assessing the potential benefits of using ICT, including eHealth, is first and foremost knowledge of the possible assistance and support it provides. Many of our informants lacking interest in ICT were not aware of its potential to help their health. Seemingly, a main reason for not using ICT was lack of knowledge of the beneficial use rather than rejection. Other authors have argued that older patients will use technology if they perceive it as useful [16]. These findings emphasize that health care professionals have an important role in promoting the benefits of using eHealth. In relation to the educative intervention we are going to develop, it is essential to provide older patients with knowledge of how this specific nutritional eHealth solution will enable them to eat sufficiently, and most importantly how sufficient food intake will have a positive effect on their health and well-being.

A prevailing finding was the informants' lack of confidence in their own competence in using ICT, and how it affected their usage. Theoretically, lack of confidence in one's own competence relates to the concept of self-efficacy, which is defined as "people's beliefs in their capabilities to produce given attainments" [34]. Self-efficacy influences individuals' health behavior intentions, and in this case engagement with an eHealth solution [34,35]. The informants' low score within the READHY dimension "Ability to actively engage with digital services" (eHLQ3) [29] supports the qualitative finding of low confidence in using ICT. The nonusers' score was significantly lower than that of the ICT users, and was also lower compared with that reported in other studies using the same instrument [36,37]. Several other studies have found that older patients' level of self-efficacy influences their use of eHealth. In a Dutch survey study (N=1014), de Veer et al [15] reported self-efficacy to be significantly correlated to older patients' intention to use eHealth applications. In another study based on data from a questionnaire (N=256) and interviews (N=15), Van Houwelingen et al [21] reported that self-efficacy predicted older patients' effort expectancy (ie, their belief in how hard or easy it is to use the technology), which was positively associated with their intention to use telehealth.

In future interventions, when introducing older patients to eHealth, it will be important to be aware of and increase their self-efficacy with use of technology. According to social cognitive theory, an individual's self-efficacy can be improved through mastery experience [34]. Therefore, a key factor in motivating older patients to engage with eHealth is to introduce it in a way that they can perceive the technology as both useful and manageable. Thus, in a hospital setting, when introducing eHealth, it is crucial to provide older patients with sufficient technical support to make them feel confident in using eHealth.

The social context such as feeling understood and having the necessary support from relatives and health care professionals influences an individual's capability to utilize eHealth [24]. The informants in our study experienced having the necessary support, including technology support from their relatives, in most cases their adult children. Moreover, they generally felt understood and supported by the health care professionals. The above qualitative findings were also reflected in the results from READHY scores, as the total sample had a high median score (above 3) on scales within the dimensions measuring their feelings of being understood and supported by health care professionals and their relatives (HLQ1 and HLQ4). It is noteworthy that the informants with a median age of 81 years had scores in the above-mentioned two scales similar to those reported in the Danish validation study covering the general population with a mean age of 53 years [38].

A lower level of health literacy among older patients has been reported [39]. This study indicated that older patients, even those with acute and chronic illness, often have health literacy resources in terms of support from their social network and trust in the health care system. However, it seems that these resources may not enable or motivate engagement with ICT. As described above, the informants lacked knowledge of the possibilities and benefits of using eHealth, despite their frequent contact with the health care system. Hence, these patients were seemingly

not informed and motivated to use ICT for health-related purposes by the health care professionals they met. This may be explained by a general perception of health care professionals that older patients are not motivated for and able to utilize eHealth [13,14]. Paradoxically, the social network appeared for some to become an obstacle to the use of ICT. In accordance with other studies [15,16], we found that helpful relatives risked taking over the tasks and thus reduced the older person's need to use ICT. Furthermore, the informants' lack of confidence in their own ICT competence was also shared by their relatives. A prevailing theme in the qualitative data was ageism, defined as "the stereotyping, prejudice, and discrimination against people on the basis of their age" [40]. The informants' perception that they, due to their high age, lacked ICT competence was in some cases confirmed by their relatives. Nevertheless, in accordance with other studies [16,21], this study showed how the informants valued the support and guidance from relatives, indicating that it is important to involve relatives when introducing eHealth to older patients. The relatives must perceive the older patients to potentially be capable of using and benefiting from eHealth. Subsequently, the educative intervention must target both patients and relatives.

An important finding in this study was the informants' perception of ICT usage leading to less personal contact with health care professionals. Consistent with other studies [33,41], the informants in our study preferred personal contact when communicating with health care professionals. The nonuse of health-related ICT was neither due to mistrust in security nor sharing data in digital systems but rather to the perception of digital communication detracting from the personal interaction with the health care professionals. Thus, older patients should be introduced to eHealth as a tool adjunct to the personal guidance and feedback from the health care professionals, enabling them to participate in their own health care. Moreover, we found that older patients may have some preferences for choice of computer devices due to health-related barriers (eg, a bigger screen due to reduced vision or a computer with a keyboard instead of a tablet due to obstacles with touch). These aspects must be considered when planning the implementation of eHealth solutions in a hospital setting to ensure older patients' successful involvement.

We found demographic differences in the samples from the two hospitals (ie, lower educational level), corresponding with differences in their READHY scores. In accordance with other studies [41], this underlines that patients with a lower

educational level may need more and individualized support to utilize eHealth.

Strengths and Limitations

One important strength of this study is that the themes appeared across the sample regardless of differences in gender, age, and socioeconomic background. The sample size was small, but nevertheless heterogeneous in terms of the older patients' gender, age, use of ICT, and educational attainment. In a small sample, heterogeneity may add strength as a pattern across variation highlights central aspects of the phenomenon [42]. Another important strength was the use of READHY as a theoretical framework, which ensured that we captured relevant perspectives in relation to competence for ICT usage. The use of a qualitative design allowed for additional perspectives to emerge. By combining the qualitative and quantitative results, we achieved a nuanced understanding of this group of patients. Furthermore, READHY is a multidimensional instrument encompassing the many aspects influencing individuals' abilities to engage with eHealth, and allows for gaining a broader understanding of older patients' resources and barriers to be addressed in an educative intervention.

This study also has some limitations. The sample consisted of 25 patients, and 60 of the 85 eligible patients were excluded due to cognitive impairment, either permanent or acute, which negatively affects the transferability of the findings. Furthermore, the informants' narratives might have been affected by their situation when they were interviewed (ie, being acutely ill and hospitalized).

Conclusions

This study indicates that a large group of older patients are potential users of ICT, but their usage showed wide variation, which was also reflected in their competencies, preferences, and attitudes toward the use of ICT. This group of patients has competencies and resources related to self-management and social support that should be utilized when introducing them to eHealth in a hospital setting. An important facilitator for motivating older patients to engage with eHealth is knowledge of the benefits derived from eHealth, and how this may assist them in managing health-related challenges. When introducing health technology to patients, health care professionals should be aware of how both their own assumptions and attitudes and those of relatives may cause a barrier, as well as an insufficient level of patients' knowledge, skills, motivation, and confidence.

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Authors' Contributions

RT performed the data collection. RT and TL performed the qualitative analysis, which was discussed continually with LK. RT performed the statistical analysis and wrote the first draft of the manuscript, which was critically reviewed by the other authors.

Conflicts of Interest

None declared.

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Abbreviations

eHLQ: eHealth Literacy Questionnaire
GP: general practitioner
heiQ: Health Education Impact Questionnaire
HLQ: Health Literacy Questionnaire
ICT: information and communication technology
READYH: Readiness and Enablement Index for Health Technology

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Original Paper

Impact of Individual, Organizational, and Technological Factors on the Implementation of an Online Portal to Support a Clinical Pathway Addressing Psycho-Oncology Care: Mixed Methods Study

Lindy Masya^{1,2}, BSocSci (C Hons), MBA; Heather L Shepherd^{1,3}, BA (Hons), DipHE, RN, PhD; Phyllis Butow^{1,3}, BA (Hons), DipEd, MCLinPsych, MPH, PhD; Liesbeth Geerligs¹, BLib Stud (Hons), MCP; Karen C Allison¹, BSc Health Sciences, MPH; Colette Dolan⁴, RN, RSCN, Grad Dip, DipPM; Gabrielle Prest^{5,6}, RN, PG (Onc Cert), BAppSc, MPH, GAICD; The ADAPT Program Group⁷; Joanne Shaw^{1,3}, BAppSc, BPsych (Hons), PhD

¹Psycho-Oncology Co-operative Research Group, School of Psychology, The University of Sydney, Sydney, Australia

²Sydney Local Health District, Camperdown, Australia

³Centre for Medical Psychology and Evidence-based Decision-Making, School of Psychology, The University of Sydney, Sydney, Australia

⁴The Kinghorn Cancer Centre, Sydney, Australia

⁵Australian College of Nursing, Sydney, Australia

⁶College of Nursing and Health Sciences, Flinders University, Adelaide, Australia

⁷see Acknowledgments

Corresponding Author:

Heather L Shepherd, BA (Hons), DipHE, RN, PhD

Psycho-Oncology Co-operative Research Group

School of Psychology

The University of Sydney

Griffith Taylor Building (A19)

Sydney, NSW 2006

Australia

Phone: 61 2 86270828

Email: heather.shepherd@sydney.edu.au

Abstract

Background: Clinical pathways (CPs) can improve patient outcomes but can be complex to implement. Technologies, such as clinical decision support (CDS) tools, can facilitate their use, but require end-user testing in clinical settings.

Objective: This study applied the Technology Acceptance Model to evaluate the individual, organizational, and technological contexts impacting application of a portal to facilitate a CP for anxiety and depression (the ADAPT Portal) in a metropolitan cancer service. The ADAPT Portal triggers patient screening on patient reported outcomes, alerts staff to high scores, recommends evidence-based management, and triggers review and rescreening at set intervals.

Methods: Quantitative and qualitative data on portal activity, data accuracy, and health service staff perspectives were collected. Quantitative data were analyzed descriptively, and thematic analysis was applied to qualitative data.

Results: Overall, 15 (100% of those invited) health service staff agreed to be interviewed. During the pilot, 73 users (36 health service staff members and 37 patients) were registered on the ADAPT Portal. Of the 37 patients registered, 16 (43%) completed screening at least once, with seven screening positive and triaged appropriately. In total, 34 support requests were lodged, resulting in 17 portal enhancements (technical issues). Health service staff considered the ADAPT Portal easy to use and useful; however, some deemed it unnecessary or burdensome (individual issues), particularly in a busy cancer service (organizational issues).

Conclusions: User testing of a CDS to facilitate screening and assessment of anxiety and depression in cancer patients highlighted some technological issues in implementing the ADAPT CDS, resulting in 17 enhancements. Our results highlight the importance of obtaining health service staff feedback when piloting specialized CDS tools and addressing contextual factors when implementing them.

KEYWORDS

decision support systems; clinical decision making; psycho-oncology; health informatics; clinical pathways; health services research

Introduction

In the last 25 years, health care has focused on improving the quality and value of care delivery through standardization of the management of specific conditions with guidelines and clinical pathways (CPs) [1,2]. CPs are structured, multidisciplinary, evidence-based management plans for a specific health condition. They outline the appropriate management with respect to clinical interventions, resources, timeframes, progress milestones, and expected outcomes, with the aim of standardizing improved co-ordination and continuity of patient care across different specialties and services [3].

The *Australian clinical pathway for the screening, assessment, and management of anxiety and depression in adults with cancer* (ADAPT CP) [4] highlights the need for routine psychological screening with appropriate follow-up for patients being treated for cancer. Cancer patients report a high unmet need for psychosocial care [5], and health professionals commonly underestimate or fail to detect patients' psychosocial concerns [6]. Screening and follow-up of anxiety and depression improve patient adherence to cancer treatment, reduce health service utilization, improve quality of life, and reduce suffering, as well as decrease the risk of patients developing a major mood disorder [7-9]. The ADAPT CP provides a structured pathway for screening, assessing, and responding to anxiety and depression in cancer care to ensure optimal patient outcomes are achieved.

However, studies across numerous health conditions confirm that guidelines and CPs are not enough to change patient care within complex health systems owing to knowledge gaps, poor communication, and insufficient implementation efforts [2,10,11]. There is growing evidence that technology can facilitate the adherence of health care organizations to CPs. Clinical decision support (CDS) tools comprise computerized alerts, reminders, and standardized data collection formats to assist health professionals with clinical decision making at the point of care [12]. Earlier CDS tools were often cost prohibitive, utilized unvalidated tools, were disruptive to clinical care processes, provided inconsistent information, or were not presented at vital points in the clinical decision-making process [13]. However, more recent CDS tools have demonstrated the benefits of improved treatment management, reduced time to treatment, standardized data collection [14], reduced clinician documentation time, lower medication errors, reduced adverse drug events [15], and greater guideline adherence [16-18]. Our group recently developed a CDS for ADAPT (the ADAPT Portal) to optimize ease of delivery of the ADAPT CP and ensure all patients receive care according to the CP.

Several theoretical models have been proposed to explain uptake and guide assessment of CDS tools, and the most widely used is the Technology Acceptance Model [19] for assessing health

care technology uptake [20,21]. This model (an adaptation of Fishbein and Ajzen's theory of reasoned action [22]) presumes a mediating role of perceived ease of use and usefulness in association with system characteristics (external variables) for explaining system uptake and usage. Perceived usefulness is defined as the degree to which a user believes that using a specific system will enhance the job performance, while perceived ease of use is defined as the degree to which a user believes that using a particular system will be effort free. External variables have been less well defined, but include aspects, such as user experience and role, and external factors in the work environment that impact usage.

This study sought to apply the Technology Acceptance Model in a pilot of the ADAPT Portal with target end users to rigorously evaluate its utility prior to a large-scale evaluation of the ADAPT CP overall. Our aim was to refine the system to best meet users' needs prior to a large-scale implementation of the ADAPT Portal. More specifically, the study aimed to evaluate the individual, organizational, and technological contexts impacting the ADAPT Portal's perceived usability, usefulness, and appropriateness within a clinical cancer service.

Methods

Study Setting and Design

The study was conducted in a cancer service within a large Australian metropolitan hospital. The cancer service elected to include patients receiving chemotherapy as part of their care in the study.

A triangulation mixed methods design [23] was employed. It combined qualitative and quantitative data sources to obtain different but complementary data to best understand these issues.

Recruitment Procedure

After senior management confirmed participation in the study and a research participation agreement was established with the cancer service, a subset of health service staff at the oncology service (purposively selected to ensure diversity in professional backgrounds and ADAPT CP roles) was invited to participate in the study. Staff received an email from the study team inviting them to participate and provide written informed consent. Participating staff were interviewed after the implementation period to capture their experience of planning for and using the ADAPT Portal within their service.

All patients commencing treatment during the study period at the site were invited to participate in the study. Interested patients provided written consent to participate in ADAPT screening and allow the research team to access their medical records.

Study Procedure

A lead team comprising management staff, nursing staff, social work staff, psychology staff, clinical system specialists, medical oncology specialists, and service improvement staff worked with the research team to tailor the ADAPT Portal to their local needs, resources, and preferences. The lead team mapped the CP and cancer service operations and compiled these into a workflow that operationalized how the ADAPT Portal would be used at the center. User training on the tailored ADAPT CP and Portal was provided to medical oncology, nursing, and allied health staff, with key ADAPT Portal users attending individual training sessions according to their roles and responsibilities in the ADAPT CP and associated tasks within the ADAPT Portal.

The ADAPT CP was then implemented for 5 months among several tumor streams within the medical oncology service. During implementation, users (health service staff and patients) had access to online, phone, and email support from the research team. After implementation, staff interviews were carried out, and portal usage and contacts with the research team were collated.

The study was approved by the Human Research Ethics Committee of the participating health care institution.

ADAPT Portal

The ADAPT Portal was developed by a multidisciplinary working group (comprising psycho-oncologists, oncologists, researchers, patient representatives, and information technology [IT] web designers and programmers) tasked with defining the ADAPT Portal's scope and functionality via agile design [24]. The goal was to operationalize the ADAPT CP [4] to make it as easy as possible for cancer services to enact within current workflows. A task analysis was conducted to identify required user interactions and data elements. This allowed tasks (dialogue between users and the system) to be grouped into modules that framed the functionality of the system (registration, screening, triage, referral, progress review, and rescreening). Components of the system that could be automated to reduce workload and facilitate health professional action where required (eg, via notifications, alerts, reminders, and reports) were identified. Complex algorithms were developed to cover all contingencies to ensure the CP was appropriately enacted for all patients. Visual mock-ups were iteratively developed and reviewed for flow and an optimal interface. User access levels were set to ensure privacy and confidentiality.

The web-based ADAPT Portal ultimately consisted of two parts. The first part was a patient-directed portal where patients verify their registration and create a password to activate their portal account, and are directed to the home page where information and resources are available. At scheduled time points, patients receive an email alert with a direct link to complete anxiety and depression screening measures and can access self-management and information resources. The second part was a health service staff portal where health service staff log in using a password, register patients who have agreed to participate in the CP with their contact details, receive alerts of patients scoring above clinical cutoffs, and are prompted to complete evidence-based

actions according to CP recommendations. Clinical staff can visually track patients' longitudinal screening data and CP progression, as well as generate reports at an individual or service level. Links to education and training resources are accessible to staff via the portal along with portal user guides and a support messaging service.

Measures

Quantitative Data Collection

ADAPT Portal user activity was reviewed to identify system functionality and uptake. A random selection of registered consenting patients' medical records was reviewed to assess the quality of data captured and discrepancies between CP documentation in the ADAPT Portal and patients' electronic medical records.

During the 5-month implementation, user support contacts were tracked, capturing the reason for contact and duration of support required. This information was reviewed and coded according to the ADAPT Portal functional domains (ie, registration, screening, referral, review, rescreening, user error, and system error) for analysis. Additionally, potential design improvements identified during lead team meetings, training sessions, and user support contacts to improve system performance and user satisfaction of the ADAPT Portal were logged throughout the study. These were reviewed by the study team and classified as *critical* (potential cause of system breakdown), *serious* (cause of frustration and nonengagement, but not critical to system function), or *minor* (mostly cosmetic issues that were not of major concern to staff).

Qualitative Data

Data were obtained via health service staff user interviews, review of user support contacts, and field observations by the ADAPT research team. Using purposive sampling, 15 health service staff members participated in semistructured interviews with an interviewer independent of the core ADAPT research team. Interviews explored perceived acceptability and utility of the ADAPT Portal, problems and challenges encountered with the system, and recommendations for improvement. Interviews were transcribed for analysis. Additional data from the staff interviews focusing on staff and organizational barriers to utilizing the ADAPT CP are published elsewhere [25]. The ADAPT research team also recorded extensive field observations after each user support contact with staff as well as during meetings with the lead team during the implementation process to record issues raised and resolutions reached.

Analysis

Quantitative data were entered into the Statistical Package for the Social Sciences (SPSS) database. Descriptive statistics (means and medians for continuous data and percentages for categorical data) were generated.

Interview transcripts were thematically analyzed by two researchers using the platform NVIVO. The two researchers independently performed initial coding to group information according to the modified Technology Acceptance Model themes [19-21] as follows: (1) individual context, individual user's perceptions about compatibility and attitude toward the

ADAPT Portal; (2) organizational context, facilitators of acceptance such as infrastructure, support, and social norms; and (3) technological context, perceived ease of use, problems reported, and change in habits resulting from using the ADAPT Portal. Any disagreements were resolved through discussion and consensus. Thematic analysis was then applied within each category to further refine the themes [26]. Each coder read six transcripts and generated a draft coding tree to capture the underlying meaning of the text, which was discussed until consensus was reached. The coding tree was iteratively revised after further coding. The text was compared and contrasted with existing themes until a final comprehensive coding structure was achieved, and the remaining transcripts were then coded.

Results

Portal Users

A total of 73 ADAPT Portal users (36 health service staff and 37 patients) were registered on the ADAPT Portal during the pilot, of whom 67 (92%) accessed the Portal.

Health Service Staff Participants

Registered health service staff included one administrator, two data managers, eight medical oncologists, 13 registered nurses, three cancer care coordinators, one clinical nurse specialist, one clinical nurse educator, four clinical psychologists, and three social workers. Of these, 15 were purposively selected (to ensure diversity of background and ADAPT CP roles) to participate in the postimplementation interview (all agreed). The interview sample included both full-time and part-time staff, who had been in their current role for an average of 3 years (Table 1).

Table 1. Interviewee demographic profile.

| Demographic | Total (n=15) |
|---|----------------------------------|
| Age, n (%) | |
| 26-50 years | 12 (80%) |
| 51-75 years | 3 (20%) |
| Gender, n | |
| Female | 15 |
| Role, n | |
| Oncologist | 1 |
| Nurse-RN ^a | 2 |
| Nurse-CNS ^b , CNC ^c , coordinator | 3 |
| NUM ^d /clinical managers | 3 |
| Clinical psychologist | 3 |
| Social worker | 1 |
| Clinical trial manager | 1 |
| Data manager | 1 |
| Duration in the current role, mean (range) | 3.4 years (5 months to 10 years) |
| Employment status, n (%) | |
| Full time | 9 (60%) |
| Part time | 6 (40%) |

^aRN: registered nurse.

^bCNS: clinical nurse specialist.

^cCNC: clinical nurse consultant.

^dNUM: nursing unit manager.

Portal Usage

Of the 37 patients registered, 16 (43%) completed screening once, with seven screening positive. In response to system alerts sent to nominated clinical staff, staff triaged all seven patients.

Following triage, the step allocation for two patients was downgraded and documented in the ADAPT Portal, two patients declined additional support, and three patients were referred via the ADAPT Portal to psychosocial services (Table 2).

Table 2. Portal user activity.

| Portal activity | Patients, n | Health service staff, n |
|----------------------------------|-------------|-------------------------|
| Number registered | 37 | 36 |
| Number accessed the portal | 35 | 32 |
| Number screened | 16 | N/A ^a |
| Total number of screening events | 17 | N/A |
| Total number of positive screens | 7 | N/A |
| Number of patients triaged | 7 | N/A |
| Number of referrals | 3 | N/A |

^aN/A: not applicable.

Support Requests and Suggested IT Improvements

A total of 34 research support requests were lodged during the 5-month implementation period, with the majority lodged by health service staff (n=32, 94%) and 2 (6%) by patients. [Table 3](#) lists the types of support requests lodged. Over a third requested clarification regarding management of patient scenarios in alignment with the CP/Portal workflow (n=13, 38%), including screening (n=5), registering (n=4), triage (n=3), and referral (n=1). The remaining support contacts lodged by

health service staff were related to user errors, such as requesting password resets (n=7, 21%), system or network errors, such as Wi-Fi dropout (n=6, 18%), health service set-up and configuration issues, such as health service staff not verifying accounts (n=3, 9%), and staff training (n=3, 9%). Usability was raised in two support requests around user habits of pressing “Enter” to move between fields, which in the ADAPT Portal, triggered field validation prompts and cleared input data from some fields.

Table 3. Summary of unplanned support contact.

| Support contact domain | Total (n=34), n |
|------------------------|-----------------|
| Workflow | 13 |
| User error | 7 |
| System & network error | 6 |
| Set-up & configuration | 3 |
| Training | 3 |
| Usability | 2 |

Regular review of support contacts and researcher observations led to 17 suggestions for improvements in the system, and of these, five were classified as critical and four were classified as serious ([Table 4](#)). Most identified improvements pertained to screening (n=5), reporting (n=4), and patient registration (n=4) functionality. However, other improvements were identified in the triage (n=2), system configuration (n=1), and

referral (n=1) functional domains. Examples included additional reporting items to record the reasons why patients did not complete screening, the ability to resend user registration emails to staff who had not verified their accounts, and allowing the “Start Screening” button to continuously display until the patient completed screening (to account for rescheduled appointments and other delays).

Table 4. Summary of system improvements.

| Functionality domain | Severity, n | | | Total (n=17) |
|----------------------|------------------|---------|-------|--------------|
| | Critical | Serious | Minor | |
| Reporting | N/A ^a | 1 | 3 | 4 |
| Screening | 2 | 2 | 1 | 5 |
| Patient registration | N/A | 1 | 4 | 4 |
| Triage functionality | 1 | N/A | 1 | 2 |
| Configuration | 1 | N/A | N/A | 1 |
| Referral | 1 | N/A | N/A | 1 |

^aN/A: not applicable.

Portal Data Accuracy

Ten patients' electronic medical records (EMRs) were compared with ADAPT Portal extracts to evaluate data capture and accuracy. These highlighted frequent missing or incorrect data on cancer diagnosis date and cancer staging in the ADAPT Portal, which occurred when these data were not available in the EMR system at the time of patient registration and were not subsequently updated in the ADAPT Portal when the information became available. CP activity recorded in the ADAPT Portal was consistent with actual psychosocial care documented in the EMR, except in two cases where the patients refused treatment. In these cases, users did not document this via the ADAPT Portal referral functionality, but rather as a free text note similar to current EMR documentation practice.

Individual Views on Usability

Interview length ranged from 16 to 50 minutes (average, 25 minutes), and the themes identified focused on usability and views of ADAPT Portal processes. Staff reported that the system was easy to use and navigate as follows:

I'm not very tech savvy, but it was fine, it was very easy. [Interview participant #5 (i5), nursing unit manager/clinical manager]

However, some staff reported difficulty logging into the ADAPT Portal owing to forgetting their passwords or poor Wi-Fi connectivity, while others reported that the time lag between training and actually using the system was too long, impacting their ADAPT Portal use confidence. Nevertheless, these challenges were quickly overcome as shown in the following comment:

By the time we got a referral we thought, oh how do we do this? How do we log in? What do we do? But, it was fine – you know, we figured it out and we could email [the support team] and she helped us. [i3, social worker]

Staff also commented positively on system support, preferring this to user guides. One staff user made the following comment:

Contact was good – if staff asked team for resources or help, response was prompt. [i15, psychologist]

Feedback on the usefulness of the ADAPT Portal for patient care was polarized. Some staff believed the ADAPT Portal did not improve on existing service processes that were well established, demonstrated in this comment:

So I think it [the ADAPT Portal] has a very good role but we're already covering those areas. [i9, nurse-clinical nurse specialist, clinical nurse consultant, coordinator]

Others reported that the ADAPT Portal was a useful mechanism to formally document psychosocial processes and remind staff that psychosocial assistance was part of standard patient care. One participant clarified their view:

I think we need to probably formalize what processes we've already got in place...I think it's important we're doing it with all patients, it's part of the ongoing

assessment of them. [i11, nursing unit manager/clinical manager]

Staff endorsed the patient resources containing local and national support information, as patients could access relevant information in one location at their own convenience. An example of a comment made by participants was:

It's useful to have and it's good for the patient. [i3, social worker]

Staff reported varied responses from patients, with most patients open to and positive about using the ADAPT Portal, but others rejected routine screening as unnecessary or too complex. One staff user observed an elderly patient having trouble screening via a tablet and decided to abandon screening.

Organizational Context

Staff reported the need for the ADAPT Portal to be linked with the existing EMR as staff already log into multiple systems for patient care and other patient screening assessments are integrated into the EMR. Participants noted that the service has undergone major technological change in the last 2 years and were therefore reluctant to undertake further technological change. This was highlighted in the following comment:

We've only had that I think, just two years or, so we've just had a massive change with that, when everybody made electronic referrals and things, and I guess maybe this was just another thing that was put onto people [i10, nurse-clinical nurse specialist, clinical nurse consultant, coordinator]

Technological Context

Staff reported that their work habits changed during the implementation period because they had to access an additional system, and their workload increased. For one user, the role expanded. Regarding the ADAPT Portal, a health service staff member made the following comment:

...was an extra thing that you're being asked to do. [i1, nurse-registered nurse]

The service found it necessary to nominate one nurse to remind staff when their patients were due for screening, despite the ADAPT Portal automatically alerting staff, to ensure screening was completed, as summarized in the comment below:

Even though there's a reminder we still forget sometimes. So, I think that one person [overseeing] is good. [i2, nurse-registered nurse]

Discussion

Principal Findings

This study is the first to review an online clinical decision support system for a CP addressing anxiety and depression screening and management (the ADAPT Portal) in an Australian cancer service. We assessed the individual, organizational, and technological contexts impacting the ADAPT Portal's perceived usability, usefulness, and appropriateness, and adjusted the system where possible to facilitate uptake in a larger implementation study. This is a critical step in the development

of new systems for use in clinical care, and is rarely evaluated qualitatively and quantitatively.

Testing the system, responding to staff support contacts, making changes to the CDS, and providing training in altered processes and components took some time and delayed patient registrations for some weeks. Ultimately, 37 patients were successfully registered, and their progress through the system was tracked.

Our study highlighted a number of usability issues, technical barriers, and training requirements that resulted in 17 improvements to the ADAPT Portal. Improvements to the ADAPT Portal allowed better recording of the rationale behind decisions and adjustment for real-world variations in patient flow through the system. These findings highlight the importance of addressing perceived usability to ensure the smooth delivery of CDS tools, such as the ADAPT CP, and mirror findings from other studies on diverse CDS tools (such as a movie recommendation system [27], social networking system [28], and health care information system [29]) that have found usability to be a key factor in determining uptake.

Nevertheless, while a number of usability issues were revealed and rectified during the study, staff on the whole had positive perceptions regarding the usefulness of the ADAPT Portal to their patients and the oncology service, which proved to be a strong motivator for ongoing use of the portal. This finding further supports the validity of the Technology Acceptance Model and reflects findings from previous studies [20,21], which have reinforced the importance of perceived usefulness in determining the uptake of health-related technology. As ease of use has been shown to impact perceived usefulness [30], both variables are clearly key to ensuring the successful introduction of technology into diverse workplaces, including the health system.

Not all staff perceived the ADAPT CP to be useful in their practice. Some believed that their existing internal processes were already effective in identifying patients requiring psychosocial support, thus rendering the ADAPT Portal unnecessary in their eyes. In contrast, 7 of 16 patients screened on the ADAPT Portal scored in the range requiring triage and referral, and may have been missed without the system in place. The PARiHS implementation framework, commonly applied to health service change efforts, suggests that staff require evidence of intervention efficacy from not only randomized controlled trials, but also their own and patient experiences, and local evidence of needs and benefits [31]. Thus, finding clear ways to communicate local benefits to staff is vital to implementation success.

While ADAPT Portal usability was addressed in this study and staff were positive about the system on the whole, some contextual issues remained as barriers. These included our inability to integrate the portal into the established electronic record management system, which increased staff burden in learning and accessing an additional system. Furthermore, staff had only recently experienced a sharp learning curve in adapting to a new EMR, reducing their capacity to learn another. James Tcheng from the US National Academy of Medicine [13] noted that technology is primarily useful for “its potential to ameliorate the burden that exponentially expanding clinical knowledge as well as care and choice complexity place on the finite time and attention of clinicians, patients, and every other member of the care team.” Thus, it remains important to ensure that technology realizes this promise by ultimately reducing burden. Furthermore, this finding reinforces the utility of measuring external factors, as well as perceived usability and usefulness in assessing technology implementation.

This study had a number of strengths, including a mixed methods design that produced a rich and complementary data set and the use of a recognized model for evaluating technology acceptance. A number of study limitations must also be considered. This was a small pilot in one urban site and may not reflect findings in other oncology services, including those in small rural areas. Implementation was for 5 months, and some issues related to technology usability may not have arisen in that time. Evaluation over a longer implementation period is required.

Conclusion

As a clinical decision support system, the ADAPT Portal achieved its goal in aligning patient care at a metropolitan cancer service with the recommendations of the ADAPT CP [4]. The pilot study results revealed that staff perceived the ADAPT Portal to be easy to use, and identified system improvements around design and additional functionality to increase usability, performance, and user satisfaction of the system at point of care. The usefulness of the ADAPT Portal was acknowledged by staff; however, some deemed it unnecessary or too burdensome, highlighting the importance of contextual factors when implementing change. The findings were invaluable for the research team in terms of refining the ADAPT Portal and structuring the implementation strategies and other supporting resources planned for evaluation in a large-scale implementation trial with cancer services [32]. Results of the large-scale implementation study will provide evidence of the effectiveness of the ADAPT Portal as a CDS system for bringing about large-scale adherence to evidence-based practice within cancer services and in differing contexts.

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Conflicts of Interest

None declared.

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Abbreviations

- ADAPT CP:** Australian clinical pathway for the screening, assessment, and management of anxiety and depression in adults with cancer
- CDS:** clinical decision support
- CP:** clinical pathway
- EMR:** electronic medical record
- IT:** information technology

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