Development of a multidimensional tool to measure individuals’ health technology readiness - The Readiness and enablement index for Health technology (READHY)

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Abstract

Background: The increasing digitalization of healthcare services with enhanced access to fast internet connections along with wide use of smartphones offers the opportunity to get health advice or treatment remotely. As a service provider, it is important to consider how consumers can take full advantage of available services and how this can create an enabling environment. However, it is important to consider the digital context and the attributes of current and future users such as their readiness, i.e. knowledge, skills and attitudes, including trust and motivation.

Objective: To evaluate how a combination of the e-Health Literacy Questionnaire (eHLQ) with selected dimensions from the Health Education Impact Questionnaire (heiQ) and the Health Literacy Questionnaire (HLQ) can be used together as one instrument to characterize an individual’s level of health technology readiness and explore how the generated data can be used to create health technology readiness profiles of potential users of health technologies and digital health services.

Methods: The instrument as well as sociodemographic questions was administered to a population of 305 citizens with a recent cancer diagnosis referred to rehabilitation in a setting that plans to introduce various technologies to assist the individuals. Properties of the READHY instrument were evaluated using confirmatory factor analysis (CFA), convergent and discriminant validity analysis and exploratory factor analysis (EFA). To identify different health technology readiness profiles in the population, the data were further analyzed using hierarchical and k-means cluster analysis.

Results: The CFA found a suitable fit for the 13 factors with only one cross loading of one item between two dimensions. The convergent and discriminant validity analysis revealed many factor correlations suggesting that, in this population, a more parsimonious model might be achieved. EFA pointed to five to six constructs based on aggregates of the existing dimensions. The results were not satisfactory, so an eight-factor CFA was performed resulting in a good fit with only one item cross loading between two dimensions. Cluster analysis showed that data from the READHY instrument can be clustered to create meaningful health technology readiness profiles of users.

Conclusions: The 13 dimensions from heiQ, HLQ and eHLQ can be used in combination to describe user’s health technology readiness level and degree of enablement. Further studies in other populations are needed to understand whether the associations between dimensions are consistent and if the number of dimensions can be reduced.
Keywords: health technology readiness; questionnaire; e-health literacy, enablement.
Introduction

The modernization of healthcare systems and the introduction of technologies are changing how healthcare systems are being improved and designed, not only in regard to quality and safety, but for reach and active reduction of health inequalities. For example, The United Nations 2030 agenda for sustainable development calls for an increased attention to how a good health status can be achieved for all people [1]. In alignment with this, the WHO’s 2016 Framework for People-Centered Health Services, emphasizes five areas of importance to address to achieve the 2030 goal; 1. empowering and engaging people and communities; 2. strengthening governance and accountability; 3. reorienting the model of care; 4. coordinating services within and across sectors; and 5. creating an enabling environment [2]. As part of the recommendations it was advocated to take advantage of new technologies and address the level of literacy amongst users. In the WHO Shanghai declaration 2016, health literacy is positioned as a critical determinant of one of three pillars for action to meet the UN Sustainable Development Goals, as health literacy empowers and creates equity. Among other things, the declaration focuses on increasing citizens’ control of their own health and its determinants through harnessing the potential of digital technology [3].

In line with these global activities, regional and national initiatives that support these goals also take place. In 2017, the EU is developing a strategy for the health sector - the Digital Single Market Strategy [4,5]. An example of a national initiative comes from Denmark, where the Regions, municipalities and a broad group of stakeholders have written a proposal for action where one of the four focus areas is to obtain a better digital support of the Danish health care system e.g. with digital solutions that support the patients’ active participation in their own treatment [6].

The above reflects the increasing digitalization of both public and private services. To achieve the potential benefits of digitalization involving patients, it is important to address the individuals’ digital readiness. Here, we define readiness in accordance with the Oxford dictionary [7] as being prepared and willing to, where prepared is interpreted as the result of an individual’s knowledge, skills and attitudes, including trust and motivation which should be considered as enabling factors as they expand the individual’s possibilities to act [8]. This is in line with the creating an enabling environment statement of the WHO Framework on integrated people-centred health services, not to be confused with the concept of health enablement which is more similar to concepts of empowerment [9].

The increasing digitalization may benefit users and bridge geographical or social gaps [10]. Digitization may, however, impose new barriers for those with low literacy, who are reluctant to use technology [11,12] or have limitations due to physical or cognitive disorders, or who don’t have the requisite skills and attitudes,
including trust and motivation (i.e. those who are not prepared and willing). Health technology has the potential to support those who have the resources and competence to take advantage of the ever-expanding market of public and private health services, and has the potential to identify, include and empower those who are disadvantaged and may be underserved if these barriers can be overcome. It is important to be able to differentiate between users with respect to their needs, resources and health technology readiness in order to be able to provide stratified solutions that address the differences in users. To be able to effectively discriminate between users, there is an imperative to fully conceptualize and measure health technology readiness of users or potential consumers of technology-assisted health care services.

Recently, authors have called for psychometrically robust instruments to assess usage of e-health systems and their impact or benefit for users [13] and their e-health literacy [14]. Despite that a recent review identified eight frameworks for eHealth readiness [15], we have not been able to identify robust, psychometrically sound instruments to assess eHealth or health technology readiness. The only two instruments we could identify were the Patient eHealth Readiness Questionnaire (PERQ) and the Service user technology acceptance questionnaire (SUTAQ). PERQ is not conceptually based or a psychometric instrument but consists of specific questions in relation to internet usage, social support, personal abilities and economy [16]. SUTAQ was developed to assess technology acceptance in the Whole System Demonstrator Project and is conceptually and psychometrically robust. The context is the users experience with a given technology, where an experience of reduced privacy and comfort predicts rejection of the technology, whereas an experience of benefits by the users lowers the likelihood of rejection. [17]

Based on three existing instruments, we propose a concept-based psychometrically sound, validated instrument, the Readiness and enablement index for health technology (READHY).

In 2015 we introduced the e-Health literacy framework (eHLF). We developed the eHLF to advance the understanding of users’ competence and experience in relation to health technologies [18]. It covers seven dimensions; 1. Ability to process information; 2. Engagement in own health; 3. Ability to actively engage with digital services; 4. Feel safe and in control; 5. Motivated to engage with digital services; 6. Access to digital services that work; and 7. Digital services that suit individual needs. In 2017, based on the eHLF, we then developed the eHealth Literacy Questionnaire (eHLQ) to enable systematic assessment of eHealth literacy [19].

The eHLQ is a multidimensional instrument that measures eHealth literacy strengths and weaknesses. The seven dimensions each have 4 to 6 items which are rated on a 4 point scale (1=strongly disagree to
Each dimension is represented by an independent scale in the eHLQ and the dimensions collectively provide a comprehensive profile of the informant. The eHLQ can be used alone in digital or technology contexts, but also adds to knowledge gained from other comprehensive questionnaires that capture patient-centered information, such as the Health Education Impact Questionnaire (heiQ) and the Health Literacy Questionnaire (HLQ). These questionnaires capture attributes related to non-digital interactions with respondents' formal and informal caregivers and their healthcare providers, their health directed behavior, their agency or ability to take action and their health literacy.

Together, the eHLF and eHLQ provide the means to understand an individual's health technology readiness by addressing both dimensions of knowledge and skills (eHLQ scales 1 to 3), user experiences (eHLQ 6 and 7), and user trust (eHLQ4) and motivation (eHLQ5). However, Gilstad et al. 2014 pointed out that eHealth literacy needs to be understood in a cultural, social and institutional context [20] and May et al. 2014 proposed that the burden of treatment may have a negative influence on the individual's mental state [21]. We recognize that these additional areas may be important to assist with fully understanding the degree to which individuals are able, prepared and willing to use health technologies, therefore supplementing the eHLQ with these additional areas should deepen our understanding of end-users readiness for full participation in health technology and to monitor how health technology potentially enables users.

The Health Education Impact Questionnaire, heiQ, comprehensibly evaluates the impact of health education interventions [22] including elements of self-reported health related behavior and empowerment [23]. The heiQ was developed by Osborne et al. in 2007 [22] and has been translated, culturally adapted and validity tested in several languages including Danish [23–26]. It has eight dimensions; 1. *Health Directed Activities*, 2. *Positive and Active Engagement in Life*, 3. *Self-monitoring and Insight*, 4. *Constructive Attitudes and Approaches*, 5. *Skill and Technique Acquisition*, 6. *Social Integration and Support*, 7. *Health Services Navigation*, and 8. *Emotional Distress*, with 40 items rated on a 4 point scale (1=strongly disagree to 4=strongly agree). The overall score of each dimension is calculated as the mean of the 4 to 7 items comprising the dimension. Each dimension is represented by an independent scale and all dimensions collectively provide a comprehensive profile of the intended proximal outcomes of health education.

The Health Literacy Questionnaire, HLQ, was considered as it measures the specific health literacy strengths and limitations of people and communities. The HLQ was developed by Osborne et al in 2013 as a multi-dimensional instrument [28] and has been translated, culturally adapted and validity tested in several languages including Danish [29]. The HLQ consists of nine dimensions, 1. *Feeling understood and supported by healthcare providers*, 2. *Having sufficient information to manage my health*, 3. *Actively managing my health*, 4. *Social support for health*, 5. *Appraisal of health information*, 6. *Ability to actively engage
healthcare providers, 7. Navigating the healthcare system, 8. Ability to find good health information, and 9. Understand health information well enough to know what to do, with 44 items. Items in the 5 first dimensions are rated on a 4 point scale (1= strongly disagree to 4= strongly agree) and items in dimensions 6-9 are rated on a 5 point scale (1=cannot do or always difficult to 5= always easy).

All three instruments have been developed using a concept mapping process and a validity-driven approach [30], in which all items are based on statements from users and clustered into concepts that are grounded in the users' collective experiences and knowledge.

To identify suitable dimensions from the heiQ and HLQ, covering social context, capabilities to handle the situation and burden of disease, to add to the eHLQ to obtain a complete health technology readiness instrument, authors LK and AK mapped the 24 dimensions of the eHLQ, heiQ and HLQ and undertook a content evaluation of the items for this purpose. The authors identified possible dimensions to be included and used information from existing literature and on-going projects known to the authors in 2016.

The authors identified 13 dimensions (Figure 1) from the three conceptually distinct instruments: The seven eHLQ dimensions describe: the attributes of the users (information and knowledge about their health and use of technology); the intersection between users and the technologies (their feeling of being safe and in control and their motivation); and users' experience of systems (they work, are accessible, and suit users' needs) [19]. From the heiQ, heiQ3 Self-monitoring and insight, heiQ4 Constructive attitudes and approaches, heiQ5 Skill and technique acquisition and heiQ8 Emotional distress, were selected as evidence was available that demonstrated that they reflect intended outcomes relevant to educational and/or technology interventions (Multimedia Appendix 1). These candidate dimensions reflect an individual's capabilities to handle their condition and emotional response. From HLQ, HLQ1 Feeling Understood and Supported by Healthcare Providers and HLQ4 Social Support for Health were selected as they add knowledge about the interaction with and impact of social and health care provider networks.

The aim of this study was to evaluate this new unified instrument, the Readiness and enablement index for health technology (READHY), with exploratory (EFA) and confirmatory factor analyses (CFA) and to suggest how the generated data can be used to assess readiness of potential users of health technologies and digital health services as well as their degree of enablement, i.e. knowledge, skills and attitudes, including trust and motivation.
Figure 1. The 13 dimensions of the Readiness and enablement index for health technology, READHY (modified from [19]). The seven eHLQ dimensions describe: the attributes of the users (information and knowledge about their health and use of technology); the intersection between users and the technologies (their feeling of being safe and in control and their motivation); and users experience of systems (they work, are accessible, and suits users’ needs). The four heiQ dimensions add knowledge about the individuals’ capabilities to handle their condition and emotional response. The two HLQ dimensions add knowledge about the individuals’ social context (represented by the circle encompassing the individual and the individual’s attributes).

Methods

Research design, setting and test population

This study was part of a bigger study investigating health technology readiness and motivation for training in the Copenhagen Centre for Cancer and Health. The study used a cross-sectional design with convenience sampling among citizens referred to cancer rehabilitation in the Centre in the period August 2016 to July 2017. Questionnaires were administered in the period October 2016 to July 2017. This setting was selected
as the organization is legally obligated to offer cancer rehabilitation and interested in the development of a
digital intervention for this context. Citizens were either asked to participate in connection with their
assessment consultation with their Centre contact person or contacted by phone by a research project
member. Exclusion criteria were age <18, insufficient cognitive function or if they could not understand
Danish. Individuals who could not be contacted by telephone were excluded after three attempts to reach
them at varying times. The citizen’s contact person also had the opportunity to decline a potential
participant from participation in the study for reasons not stated. Out of 857 citizens referred in the project
period, 430 were asked to participate. Out of these, 62 were excluded and 63 refused to participate
resulting in 305 participants. We considered 300 an adequate sample size for the CFA [31–33]. All
participants answered a background information questionnaire, the Behavioral Regulation in Exercise
Questionnaire, BREQ-2, and the READHY instrument. Participants had a mean age of 58 years (ranging from
18-90 years), 70.8% were women and 81.6% owned a smartphone. The participants filled out the
instrument in paper form. If the participant wished, a research project member was present to clarify
questions or assist the participant. The 13 dimensions READHY instrument consisting of 65 items rated on a
4 point scale (1=strongly disagree to 4=strongly agree) was administered in the same order to all
informants. The items were grouped according to the instrument they belong to and administered in the
same sequence as in the original instruments. The overall score of each dimension was calculated as the
mean of the 4-6 items comprising the dimension. Missing items; if ≥ 50% of the items in a dimension were
answered an average for the dimension was calculated based on the filled in items.

Statistics

**Evaluation of the properties of READHY using Confirmatory factor analysis (CFA)**

Factor analysis of the selected 13 heiQ, HLQ and eHLQ scales was based on a sequence of analyses that
followed and extended the general idea of ‘semi-confirmatory’ factor analysis suggested by R. P. MacDonald
[34]. All analyses were conducted with Mplus 8 [35] mostly using the exploratory structural equation
modeling (ESEM) program feature with polychoric correlations, weighted least squares mean and variance
adjusted (WLSMW) estimation appropriate for ordinal data, and Geomin rotation when exploratory factor
analysis (EFA) was applied. The sequence of analyses was as follows: (1) The first analysis was a CFA
hypothesizing 13 factors, followed by an analysis of the convergent/discriminant validity, using Fornell &
Larker’s criteria [36,37] for establishing convergent and discriminant validity, of the 13 factors based on the CFA
results. If the analysis of convergent/discriminant validity suggests that some of the scales are showing
insufficient discriminant validity a more parsimonious factor structure might yield a satisfactory fit to the
data. (2) The CFA and analysis of convergent/discriminant validity was followed by a full EFA. When a scree
slope from this analysis clearly suggests that as a more parsimonious factor solution might be a satisfactory account for the relationships between the 13 scales, a series of EFA runs are applied to extract a smaller number of factors. (3) An ESEM model was then hypothesized based on the previous analyses. (4) A final CFA to confirm the revised factor structure and estimate its fit to the data completed the sequence.

Model goodness-of-fit was assessed by the Root Mean Square Error of Approximation (RMSEA); Comparative Fit Index (CFI); and the Tucker-Lewis Fit Index (TLI) [38]. We regard a well-fitting model as one where the RMSEA is <0.06 and the CFI and TLI are >0.95, while a value of <0.08 for the RMSEA was taken to indicate a "reasonable" fit [39–42].

Cluster analysis
The READHY instrument is intended to characterize populations stratified by their level of health technology readiness. Inspired by the creation of personas in IT systems development [43] and by the recently published model for Ophelia (OPTimise HEalth Literacy and Access) process [44,45] we explored how dimensions can be used for modeling profiles or data to develop personas.

We applied a combined approach using hierarchical analysis to perform an exploratory evaluation and then the k-means method to evaluate the strength of the resulting number of clusters and to characterize the subgroups. Cluster analysis was performed using IBM SPSS statistics version 22. The hierarchical approach using Ward's method for linkage [46] was performed for a range of cluster solutions. The appropriate number of clusters for the dataset was guided by examining the agglomeration schedule to identify the demarcation point and the dendrogram to identify when the variance of the dimensions within the clusters increased. The standard deviations for the group mean profiles of the different cluster solutions were also compared as standard deviations >0.6 could indicate that there are still significant subgroups within the cluster [45]. Guided by the findings of the hierarchical cluster analysis, a k-means cluster analysis of the dataset was performed. As opposed to hierarchical clustering methods were cases are consecutively added to existing clusters, the k-means algorithm constantly reassigns cases to clusters independently of former assignments to minimize the within-cluster variation [47,48]. The appropriateness of the k-means cluster solution was evaluated by the number of dimensions with a standard deviation >0.6 and by examining the one-way analysis of variance (ANOVA) performed for each dimension to see if there where variables not contributing to cluster separation (insignificant F-values).

To confirm the results from the hierarchal analysis, the above was performed and compared for a range of k-means cluster solutions, lying around the demarcation point of the hierarchical analysis, to identify the best fit. Clustering was also used to identify individuals belonging to certain sub-groups which were
hypothesized to be present in the sample population. For this purpose a higher number of clusters may be appropriate. This was explored by performing a range of e.g. 5-10 cluster solutions and examining the attributes of the resulting clusters.

**Ethics**

The project complied with the Helsinki declaration and was approved by the Danish Data Protection Agency (2015-55-0630). Under Danish law, permission from an ethics committee was not required because biological material was not used in the study. All participants received oral and written information about the survey and were informed that their participation was voluntary, that they were ensured anonymity and that all data would be handled confidentially. Written informed consent was obtained from all participants.

**Results**

**Evaluation of the properties of READHY using CFA**

The 13 factor CFA, demonstrated a reasonable fit for the 13 factors (RMSEA = 0.049 (95% CI = 0.046-0.052); CFI = 0.94; TLI = 0.935). With the exception of heiQ3 and eHLQ6, all scales were well identified by the hypothesized items. Only item 10 cross-loaded between heiQ3 and heiQ8 (see Multimedia Appendix 2).

For two scales, heiQ3 and eHLQ6, the average variance extracted (AVE) was <0.5 (Fornell and Larker’s first criterion) and thus where convergent validity was questionable (Multimedia Appendix 3). Also, following Fornell and Larker’s second criterion, there were 9 pairs of scales that showed insufficient discriminant validity where the AVE of one or the other in the pair was less than the variance shared between the two (heiQ3 and heiQ5; heiQ3 and eHLQ2; eHLQ1 and eHLQ5; eHLQ1 and eHLQ 6; eHLQ2 and eHLQ6; eHLQ3 and eHLQ6; eHLQ5 and eHLQ6; eHLQ5 and eHLQ7; eHLQ and eHLQ7). eHLQ4 showed good discriminant validity, while eHLQ2 was problematic in relation to eHLQ6 because of the low convergent validity of eHLQ6. This suggests that, in this population, a more parsimonious model with a fit similar to the 13-factor model might be achieved. As a consequence, an EFA was performed. The scree slope suggested that a 5 or 6 factor solution might be suitable (Multimedia Appendix 4). Using “close-fit” criteria, the 6-factor solution was a satisfactory fit to the data (RMSEA = 0.046 (95% CIs = 0.043-0.053); CFI = 0.953; TLI = 0.943). The factor loading pattern from this solution generally paralleled the results of the convergent/discriminant analysis of the 13 factor CFA solution. Items from heiQ scales 4 and 8 loaded on one bi-polar factor that contrasted the two constructs while items from heiQ scales 3, 4 and 5 loaded on another factor. One resolution of this pattern would be to hypothesise 3 discrete heiQ factors consisting of heiQ 4 items, heiQ 8 items, and items from heiQ 3 and 5 combined. Items from HLQ1 and 4 loaded on the same factor, while another factor was
constituted only by secondary loadings from HLQ4 items. The eHLQ items separated into one large factor and a smaller factor constituted by eHLQ 4, some eHLQ6 items and, secondarily, two eHLQ7 items.

Given the lack of clarity in this solution the EFA analyses were extended to 7 and 8 factors, and subsequently an 8-factor ESEM model. The ESEM model posited 3 factors comprised of heiQ scales (heiQ 4 and 8 separately and heiQ 3 and 5 combined) and 2 of HLQ scales (HLQ1 and HLQ4 separately). These were “CFA” factors in that cross-loadings among them were not allowed. Additionally, the model posited 3 factors comprised of eHLQ items that were fitted by an “EFA” component with Geomin rotation. The fit of this 8-factor ESEM model was good by all close-fit criteria (RMSEA = 0.043 (95% CIs = 0.040-0.046); CFI = 0.953; TLI = 0.950). This model clearly confirmed heiQ 4, 8, and 3-5 combined, and HLQ 1 and 4 as independent factors. It also suggested that eHLQ1, 3, 5, 6, and 7 items largely combined into one factor with items from eHLQ2 and eHLQ4 identifying separate factors. A final CFA analysis was conducted to confirm this 8-factor model (Multimedia Appendix 5). All items were required to load on only one factor as suggested by the ESEM analysis with one exception; eHLQ item 33 was allowed to load on both the “omnibus” eHLQ factor and the eHLQ factor comprised of eHLQ4 items. Fit was satisfactory given the extensive model constraints of only one allowed cross-loading and no residual correlations (RMSEA = 0.053 (95% CIs = 0.051-0.056); CFI = 0.927; TLI = 0.923). All hypothesized loadings, with 3 exceptions (including item 33), were >0.4 and all but 6 loadings were >0.5. Item 33 originally an eHLQ scale 6 item was, in this sample, clearly associated with eHLQ 4 items.

Cluster analysis
The hierarchical cluster analysis suggested a 4-cluster solution as appropriate and the characteristics of three, four, and five k-means cluster solutions were explored. Based on the k-means evaluation it was concluded that in this dataset a 4-cluster solution was the best fit. The magnitude of the F values from the analysis of variance performed on each dimension indicated that, in particular, eHLQ dimensions discriminated between the clusters. The sub-groups of the 4-cluster solution were distinct in their READHY profiles (Figure 2). The heiQ and HLQ scales distinguished between profiles 1 and 2 (high) on the one hand and profiles 3 and 4 (lower) on the other. The eHLQ scales identify 3 groups – profile 1 (high on all), profile 2 and 3 (middle on all), and profile 4 (low on 5). Profile 4 was lowest on the 5 scales that seem to be most clearly measuring motivation, access and capability with digital health services. Profile 1 had the highest smartphone ownership, was the youngest and had the lowest number of chronic conditions. Profile 4, with the lowest scores, was the oldest and least likely to own a smartphone (Table 1).
Figure 2. Four health technology readiness profiles based on cluster analysis of questionnaires administered to 305 people with a recent diagnosis of cancer. HeiQ8 was reverse scored so that a high score means low level of distress.

Table 1. Demographic characteristics of individuals across four and eight health technology readiness profiles

<table>
<thead>
<tr>
<th></th>
<th>Age (mean)</th>
<th>Own a smartphone (%)</th>
<th>Number of chronic conditions (other than cancer) (mean)</th>
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<tbody>
<tr>
<td><strong>4 cluster profiles</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Profile 1</td>
<td>53.9</td>
<td>92</td>
<td>0.59</td>
</tr>
<tr>
<td>Profile 2</td>
<td>58.1</td>
<td>79</td>
<td>0.65</td>
</tr>
<tr>
<td>Profile 3</td>
<td>57.9</td>
<td>89</td>
<td>0.73</td>
</tr>
<tr>
<td>Profile 4</td>
<td>67.8</td>
<td>42</td>
<td>1.34</td>
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<tr>
<td><strong>8 cluster profiles</strong></td>
<td></td>
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<tr>
<td>Profile 1</td>
<td>55.1</td>
<td>92</td>
<td>0.58</td>
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<tr>
<td>Profile 2</td>
<td>56.0</td>
<td>89</td>
<td>0.65</td>
</tr>
<tr>
<td>Profile 3</td>
<td>56.9</td>
<td>88</td>
<td>0.70</td>
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<tr>
<td>Profile 4</td>
<td>61.2</td>
<td>65</td>
<td>0.73</td>
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<tr>
<td>Profile 5</td>
<td>62.8</td>
<td>72</td>
<td>0.56</td>
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<tr>
<td>Profile 6</td>
<td>55.3</td>
<td>88</td>
<td>1.05</td>
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<tr>
<td>Profile 7</td>
<td>70.9</td>
<td>53</td>
<td>1.35</td>
</tr>
<tr>
<td>Profile 8</td>
<td>58.9</td>
<td>29</td>
<td>1.29</td>
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</tbody>
</table>
When clustering was conducted to identify individual belonging to certain sub-groups, an eight-cluster solution (Figure 3) revealed two profiles, 6 and 8, that scored low in the heiQ scales compared to the other clusters. Profile 8 was low on HLQ4 Social Support for Health and all eHLQ scales, while profile 6 was in the middle range on HLQ and eHLQ scales. Profile 7 was very low on four of the five eHLQ scales associated most directly with ehealth motivation, access and capability and middle to relatively high on heiQ and HLQ scales. Profile 1 was high in eHLQ scales and relatively high in the heiQ and HLQ scales. Profile 8 had a higher number of chronic conditions and was least likely to own a smartphone (table 1). Profile 6 had a high smartphone ownership and an average of one additional chronic condition. Profile 7 was the oldest, had the highest number of chronic conditions and less likely to have a smartphone. Profile 1 was the youngest, had the lowest number of chronic conditions and the highest smartphone ownership.

Figure 3. Eight health technology readiness profiles based on cluster analysis of questionnaires administered to 305 people with a recent diagnosis of cancer. heiQ8 was reverse scored so that a high score means low level of distress.

Discussion
This study presents an instrument to understand user health technology readiness as a broad concept underpinned by e-health literacy, social interactions and the user’s mental state. The proposed combination of eHLQ with selected dimensions from the heiQ and HLQ constitutes a potentially useful instrument. Using
an a priori model, a series of analyses identified indicators and potentially relevant profiles of users and potential users of health technologies and digital health services. These indicators constitute readiness, i.e. knowledge, skills and attitudes, including trust and motivation.

**Evaluation of the properties of READHY using CFA**

Within our current data, a large group of people with a cancer diagnosis engaged in rehabilitation services, we found discriminant validity between some of the scales was not sufficient, suggesting that a more parsimonious model, with fewer items and scales, might be available. However, we were not able to find a better fit although our results indicate clear grouping of some dimensions. One example is the high correlation between heiQ3 *Self-monitoring and insight* and heiQ5 *Skill and technique acquisition*. This could either be due to the two dimensions capture the same construct, or that one (heiQ 5) might cause the other (heiQ3), thus a high correlation between them is observed but they are difference constructs and different interventions would affect changes in these dimensions. Likewise, the connection between eHLQ1, eHLQ3, eHLQ5, eHLQ6 and eHLQ7 may be explained by a causal pathway, i.e., having the personal knowledge and skills to engage with digital services and information and having access to systems that works and motivates you. While there appears to be some overlap between some of the 13 scales selected, and potential causal hypothesis can be drawn from the data, the 13 factor model works satisfactorily notwithstanding some factor collapse. If such a pattern is replicated in other patient groups in other settings, particularly among the eHLQ scales, a reduced number of scales might be appropriate for future use, particularly in population studies where questionnaire length may be important. Careful testing of the READHY in other settings receiving technological interventions, such as people with complex conditions e.g. chronic obstructive pulmonary disease, diabetes or cardiac heart failure, will provide important empirical information that will assist with reducing the total number of items of the READHY. However, a premature reduction of dimensions may omit information critical in other contexts, e.g., when robust interventions are introduced and computer media or system services are changed.

**Cluster analysis**

The combination of hierarchical and k-means cluster analysis is a way of identifying clusters of individuals with respect to their attributes in relation to health technology. The clusters can be further explored by adding disease specific and sociodemographic data. These different profiles can be addressed in the form of tailored introductions to technology, educational programs or variations in user interfaces. In addition, these groups can be used to understand the individual's attitude and experiences in relation to health technology and their emotional well-being and impact of their condition. For a health technology design or
service design process a lower number of clusters would be appropriate while separating users into further clusters can help understand how different user types can be supported in their use of technology.

The profiles identified in the cluster analysis may be useful for identifying those who are in risk of being marginalized or are in need of particular interventions. We identified such a group in the 8 cluster analysis. In this sub-group (see Profile 8, Figure 3), individuals have high emotional distress and may need assistance to learn to cope with and manage their situation to reduce the burden of their condition before being ready to engage with digital services/technologies. Although only seven individuals belonged to this group, they are likely to be under represented in the sample, given the recruitment process, and they represent at least 2% of the population and thus a considerable number of individuals in a national or regional perspective. This group may well be found to be higher users of healthcare services as their chronic conditions progress. It is important to characterize high risk groups which is reflective in important programs such as Denmark’s and other countries focus on interventions for the 1% of the population that accounts for almost a third of the health care expenses [49–55]. This data driven approach may be a strong tool to identify particular sub-populations to tailor specific actions and/or interventions to particular groups. This approach has been effectively incorporated into health system improvement initiatives such as the OPtimising HEalth Literacy and Access (Ophelia) process [44,45].

Health technology readiness

The READHY instrument offers a means to understand users of health technology and provides a measure of health technology readiness of the users. In comparison, Technology Readiness Levels, TRL, are usually used to describe the maturity of a technology [56]. READHY addresses the complementary situation, how ready and able the user is to engage with and take advantage of technologies. This adds to the understanding of the complex situation of a user’s interaction with digital tools in a health context. Factors of relevance for successful usage of technologies include technology, user and interface, and can be described as; 1. Technology maturity as described by the TRL, 2. User knowledge, skills and attitudes to use the technologies, which can be described by an eHealth literacy profile supplemented with the proposed dimensions from the heiQ and HLQ, and 3. The interface between the user and the technologies which is commonly assessed using usability tests. In this ecosystem, we expect the READHY will deepen the understanding of the relation to formal and informal caregivers, as well as the understanding of users’ (non-users and future users) capacity to cope and manage their condition in current and emerging technological environments.
Strengths and limitations of the study
A strength of the study is the way we sought to minimize missing people with low literacy as we ensured respondents had the opportunity to have the instrument read aloud and filled out for them by a project member. A limitation to this study is the exclusion of ethnic minorities. Furthermore, it has been shown that referral to the Copenhagen center for Cancer and Health is not equally distributed by socioeconomic group. Higher educational level is associated with a higher rate of referral to rehabilitation services [57].

Perspectives
We suggest the READHY instrument can be used to; 1. Characterize users and group them according to their attributes, 2. Design tailored interventions and education programs, 3. Evaluate, from an individual and organizational perspective, the degree to which new technologies or services enables target groups.

Conclusions
To advance the reach and impact of health systems it is critical that digital health becomes widely embraced. However, to build digital health services that meet the demands of WHO’s 2016 Framework for People-Centered Health Services, greater attention needs to be paid to the readiness of individuals and communities to use the rapidly growing digital health opportunities. The READHY instrument, with further testing in a wide range of settings, may be a promising tool to provide technologists, researchers, health care providers and policymakers with robust information to ensure fit for purpose and inclusive digital health systems are developed and evaluated across healthcare systems.

Acknowledgements
This study was supported by TrygFonden. TrygFonden had no role in the study design, collection, analysis or interpretation of the data, writing the manuscript, or the decision to submit the paper for publication. The eHLQ is available through license by either Deakin University or by University of Copenhagen. The HLQ and heiQ are available through license by Deakin University.

Conflicts of interest
The authors have no conflicts of interest to declare.

Multimedia Appendix
Multimedia appendix 1. Overview of heiQ dimensions affected during interventions.
Multimedia Appendix 2. CFA for the 13 factor model.
Multimedia Appendix 3. Convergent/discriminant validity for the 13 factor model.
Multimedia Appendix 4. Scree plot for the exploratory factor analysis.
Multimedia Appendix 5. CFA for the 8 factor model.
**Abbreviations**

AVE  average variance extracted  
CFA  Confirmatory Factor analysis  
CFI  comparative fit index  
CI  confidence interval  
EFA  exploratory factor analysis  
eHLF  eHealth Literacy Framework  
eHLQ  eHealth Literacy Questionnaire  
ESEM  exploratory structural equation modeling  
heiQ  health education impact questionnaire  
HLQ  Health Literacy Questionnaire  
Ophelia  OPtimising HEalth LIteracy and Access  
PERQ  Patient eHealth Readiness Questionnaire  
READHY  Readiness and enablement index for health technology  
RMSEA  root mean square error of approximation  
SUTAQ  Service user technology acceptance questionnaire  
TLI  Tucker-Lewis fit index  
TRL  Technology Readiness Level  
WLSMW  weighted least squares mean and variance adjusted

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