2017

# Discovering Design Principles for Health Behavioral Change Support Systems: A Text Mining Approach

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# Discovering Design Principles for Health Behavioral Change Support Systems: A Text Mining Approach

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Behavioral Change Support Systems (BCSSs) aim to change users' behavior and lifestyle. These systems have been gaining popularity with the proliferation of wearable devices and recent advances in mobile technologies. In this article, we extend the existing literature by discovering design principles for health BCSSs based on a systematic analysis of users' feedback. Using mobile diabetes applications as an example of Health BCSSs, we use topic modeling to discover design principles from online user reviews. We demonstrate the importance of the design principles through analyzing their existence in users' complaints. Overall, the results highlight the necessity of going beyond the techno-centric approach used in current practice and incorporating the social and organizational features into persuasive systems design, as well as integrating with medical devices and other systems in their usage context.

CCS Concepts: • **Information systems → Data analytics**; • **Computing methodologies → Topic modeling**; • **Applied computing → Consumer health**

Additional Key Words and Phrases: Mobile diabetes apps, online user reviews, topic mining, Latent Dirichlet Allocation (LDA)

**ACM Reference Format:**
Mohammad A. Al-Ramahi, Jun Liu, and Omar F. EL-Gayar. 2017. Discovering design principles for health behavioral change support systems: A text mining approach. ACM Trans. Manage. Inf. Syst. 8, 2–3, Article 5 (June 2017), 24 pages.
DOI: http://dx.doi.org/10.1145/3055534

## 1. INTRODUCTION

Persuasive systems, also referred to as Behavioral Change Support Systems (BCSS), are "socio-technical information systems with psychological and behavioral outcomes designed to form, alter or reinforce attitudes, behaviors or an act of complying without using coercion or deception" [1]. This definition includes promising outcomes for BCSSs that make them especially useful in certain areas such as healthcare. Due to their role in fostering improved health and healthier lifestyles, health BCSSs are considered nowadays one of the most prominent areas for future healthcare improvements [1]. Indeed, health BCSSs have been reported to produce positive results in areas such as management of smoking cessation, hazardous drinking, obesity and diabetes [2]. These technologies can be delivered via Web, SMS, social networking systems, or by other state-of-art technological means such as health interventions available via mobile devices.

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DOI: http://dx.doi.org/10.1145/3055534

In the last decade, the exponential growth in smartphone technology has resulted in opportunities to encourage and support health care consumers to adopt healthy behaviors and to self-manage chronic diseases. Mobile health applications (often referred to as apps) have been proved to be effective in inducing healthy behavior (e.g., encouraging smoking cessation) and improving disease management (e.g., improving management of diabetes) [3]. Despite their potential benefits and growing popularity, healthcare apps as health persuasive technology still have not been used to their fullest strength. According to Mclean [4], 26% of healthcare apps are downloaded with only one use, 74% of them drop out by the tenth use. Only 5% of health apps are still in use 30 days after download [5]. The literature of consumer health IT applications posits inadequate design as a reason for inadequate use of health apps. In an exhaustive review of consumer health informatics (CHI) applications, Gibbons et al. [6] identified design barriers that have prevented the adoption of consumer health IT applications. Those barriers not only include technological issues such as incompatibility with current care practices but span issues across social and technical boundaries. It is hence important to adopt a holistic socio-technical perspective to develop mobile apps for self-care and patient empowerment. In particular, to build successful and sustainable health apps, developers have to bring users into their design so that they can identify flaws and uncover needed workflow and interface functions [7].

To address the aforementioned issues, Oinas-Kukkonen and Harjumaa [8] proposed a set of design principles for persuasive systems. The proposed design principles rely mostly on expert intuition and analysis of prior research rather than being informed by actual usage and users' experiences. Other studies in the field (e.g., [9, 10]) often focus on investigating the effectiveness of persuasive systems design rather than developing design principles for enhancing the effectiveness.

Nowadays, the advances of Web 2.0 technologies have enabled consumers to easily and freely exchange opinions on products and services on an unprecedented scale (volume) and in real time (velocity). Online user review systems provide us with one of the most powerful channels for extracting user feedback that can help enhance persuasive systems design. In the e-commerce domain, user reviews have long been widely recognized as a crucial factor that influences product sales (e.g., [11]) and shapes consumers' purchase intention (e.g., [12]). In the domain of health BCSSs, analyzing users' reviews has the potential to greatly inform developers of consumers' preferences and how they engage with health BCSSs and provide opportunities for further enhancing their efficacy. However, up to now, very few efforts have been made to extract knowledge from large-scale online reviews of mobile health apps to help understand consumer satisfaction and its antecedents. Although 72% of mobile health app vendors have used analytics and testing tools to develop, test, market and monitor the performance of their apps [13], most mobile health app developers have ignored users' needs by designing tools that primarily reflect the imperatives of clinicians with little or no attention to users' experiences, wishes or requirements [14].

In this study, we systematically analyze users' reviews and develop design principles from the actual use of BCSSs. We use diabetes mobile applications as an instance of health BCSS and develop design principles based on a systematic analysis of users' reviews. Diabetes is a chronic illness that requires continuing medical care and ongoing patient self-management education and support to reduce the risk of long-term disability and prevent complications [15]. Existing research such as Or and Tao [16] has proved that the use of health mobile apps improves outcomes in diabetes patient self-management. However, the current diabetes mobile apps have failed to achieve their full potential, and they are either too narrow or too technical to become a daily companion for consumers [17]. Therefore, in this research, we aim to extract insights from users' reviews of diabetes mobile apps. Given the huge amounts of the data available online, we propose a new method that utilizes text-mining, specifically topic modeling, to analyze the contents of user reviews and identify design principles for health behavioral change support systems. The main contributions of this study are summarized as follows:

(1) From a theoretical perspective, the findings of this study inform the design theory of persuasive systems. Specifically, this study develops new persuasive design principles and provides support to some existing theoretical persuasive design principles developed by Oinas-Kukkonen and Harjumaa [8]. Different from the existing research that focuses on the technical issues, our research advocates a socio-technical design of BCSSs. We develop design principles that foster the integration and communication between the various components within the ecosystem that is primarily informed by the key beneficiaries of such systems.
(2) From a methodological perspective, this research introduces a new method that leverages text analytics techniques to discover design principles from online user-generated content in the health care domain. As far as we know, this is the first work that leverages online user review content and topic mining in the field of persuasive systems. The proposed method could also be deployed in other domains to inform pertinent theories based on the wealth of user-generated input made available through user reviews.
(3) From a practical and applied research perspective, the findings of the study highlight the importance of integrating users with other IT systems and medical devices in their usage context as well as incorporating the technical and social support features into design. The study also provides developers with insights into the user-reported issues of health apps, along with their frequency, impact, and relationship to user ratings. These insights can help developers better prioritize the relevance and application of design principles while designing their apps.

## 2. RELATED WORK AND BACKGROUND

### 2.1. Health Behavioral Change Support Systems (BCSSs) Design

Oinas-Kukkonen and Harjumaa [8] proposed a set of design principles classified into four categories including *primary task support*, *dialogue support*, *system credibility support,* and *social support*. However, the proposed design principles appear to be based on experts' intuitions and an analysis of prior research rather than a systematic analysis of users' feedback from the actual use of BCSSs. Other studies often focus on investigating the effectiveness of persuasive systems design (e.g., [9, 10]) rather than developing design principles for enhancing the effectiveness.

Due to the promising influence of smartphone-based technologies in supporting healthy lifestyle and self-care practices, a number of researchers have explored design principles that encourage on-going and sustainable use of these persuasive systems. For example, Chomutare et al. [18] studied the design features of mobile applications for diabetes care and compared them with the clinical guidelines for diabetes self-management. They found that the integration of mobile applications with social media is missing in most of the current apps.

Although health BCSSs help enhance patients' self-care, these technologies are still not always accepted by patients [19]. The research into healthcare information and management systems thus far has mostly focused on electronic medical records and health information libraries with less attention to tools developed for patients' behavioral change [1]. In fact, a systematic review of the literature regarding patient acceptance of Consumer Health Information Technology (CHIT) conducted by Or and Karsh [19] revealed that few studies tested the impact of *organizational* or *environmental factors* on acceptance while *social factors* were not examined. Sarnikar et al.

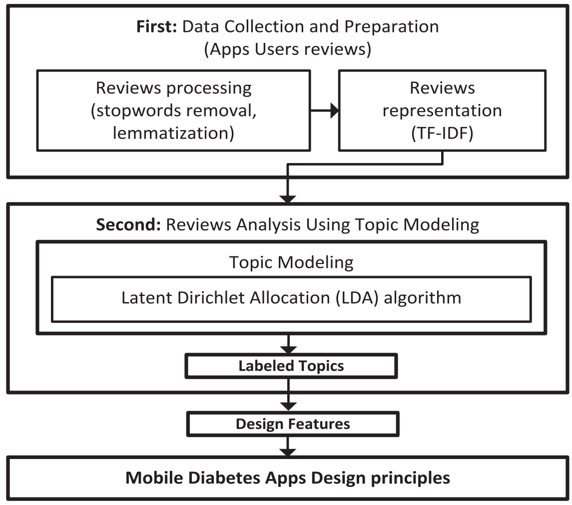


Fig. 1. Overview of our text-mining-based approach.

[20] proposed a model for eliciting requirements of socio-technical systems and suggested that further research is needed to leverage actual user feedback in identifying socio-technical design guidelines.

Overall, to build successful and sustainable health apps, developers have to bring users into their design so that they can identify flaws and uncover needed workflow and interface functions [7]. Little research, however, has developed persuasive design principles based on user feedback. Designing effective persuasive systems must be driven by paramount consideration of what the users need. After all, user acceptance/adherence is the key to the success of health BCSSs. These technologies cannot help facilitate self-monitoring and self-management or improve patients' health outcomes when patients do not accept them. To address this "gap" in the existing research, we aim to use a text mining approach to help identify design features from online user reviews, and develop design principles for health BCSSs based on the discovered features.

### 2.2. The Impacts of User-Generated Content

Several researchers in the areas of social media and e-commerce have studied the effects of user-generated content such as online users' reviews and rating systems on product sales and consumers' purchase intention. The findings of the existing research have demonstrated that analyzing and measuring these electronic word-of-mouth (eWOM) messages is quite valuable in product design, sales prediction, marketing strategy, and other decision-making tasks (see Appendix A). However, to our knowledge, no research to date has looked at online user reviews in the context of health behavioral change support systems (HBCSS). User reviews implicitly communicate users' satisfaction/dissatisfaction based on actual usage experience and may provide a good opportunity for extracting design dimensions that can strongly influence users' satisfaction/dissatisfaction and then inform the design of these systems.

## 3. TEXT-MINING-BASED APPROACH AND RESEARCH FRAMEWORK

Figure 1 shows the architecture of our text-mining-based approach.

We propose to use an unsupervised topic model for discovering design features from online user reviews of the diabetes applications. Below, we first discuss the data collection and preparation process. We then explain the topic modeling technique used to

Table I. Summary of Data Collected

| Count of apps | Count of user reviews | Mean | Std Dev | Median | Min | Max |
|---|---|---|---|---|---|---|
| 30 | 4,218 | 140.6 | 116 | 100 | 50 | 450 |

extract design features from online users' reviews. Finally, we discuss our method for developing the design principles.

### 3.1. Data Collection and Preparation

The data for this study was collected from Apple iTunes store[1]. First, the keyword "diabetes" was used to retrieve all diabetes-related applications. Second, we filtered the applications. To be included in the study, an application must provide functions to support diabetes self-management. We excluded applications without English-language user interfaces as well as those intended exclusively for health care professionals. As a result, 30 applications were selected. Please see Appendix B for the names of these 30 applications. For each iOS application, the reviews posted by the users were gathered using the Apple store API. Through this process, we obtained our data set consisting of 4,218 reviews (140.6 reviews per app on average). Table I summarizes the collected data.

When preprocessing the data, we removed stop words, performed lemmatization, which means converting words in inflected forms (e.g., plural nouns and past-tense verbs) to their original forms, and represented each document using the well-known Term Frequency Inverse Document Frequency (TF-IDF) weighting scheme [21].

### 3.2. Topic Modeling: LDA

Topic models are statistical-based algorithms for discovering the main themes (i.e., set of topics) that describe a large and unstructured collection of documents. Topic models allow us to summarize textual data at a scale that is impossible to be tackled by human annotation. We selected the Latent Dirichlet Allocation (LDA) model, the most common topic model currently in use, due to its conceptual advantage over other latent topic models [22]. The model generates automatic summaries of topics in terms of a discrete probability distribution over words for each topic, and it also infers per-document discrete distributions over topics. The interaction between the observed documents and hidden topic structure is manifested in the probabilistic generative process associated with LDA. This generative process can be thought of as a random process that is assumed to have produced the observed document [23]. To illustrate the results of LDA, Let $M$, $K$, $N$, and $V$ be the number of documents in a collection, the number of topics, the number of words in a document, and the vocabulary size, respectively. The first result is an $M \times K$ matrix, where the weight $w_{m,k}$ is the association between a document $d_m$ and a topic $t_k$. In our case, the documents are user reviews for diabetes apps (i.e., we integrated the reviews of all apps in a big data file and treat each user review as a single document) ($M = 4{,}218$). The second result is an $N \times K$ matrix, where the weight $w_{n,k}$ is the association between a word $w_n$ and a topic $t_k$. The notations $Dirichlet(\cdot)$ and $Multinomial(\cdot)$ represent Dirichlet and multinomial distribution with parameter $(\cdot)$, respectively. The graphical representation of LDA is shown in Figure 2, and the corresponding generative process is shown below:

(1) For each topic $t \in \{1, \ldots, K\}$
  (a) draw a distribution over vocabulary words
    $\boldsymbol{\beta}_t \sim Dirichlet(\boldsymbol{\eta})$
(2) For each document d,

[1]The date of collecting data is January 11, 2015.

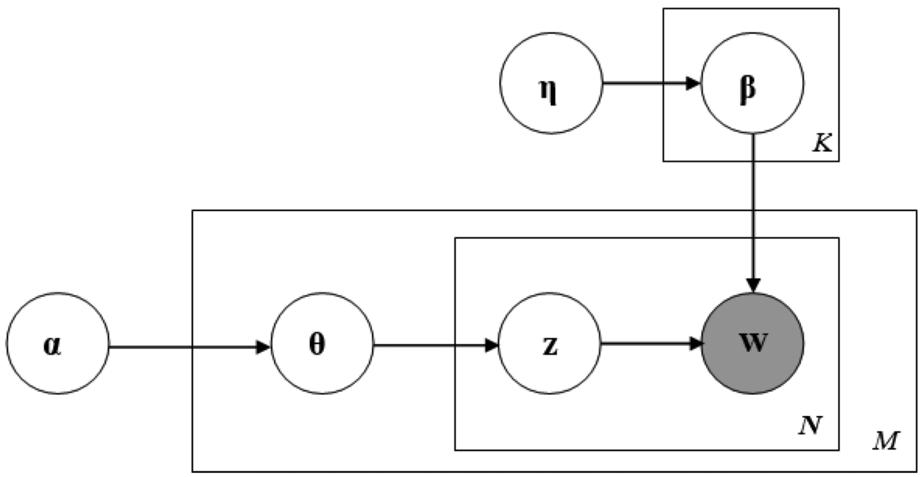


Fig. 2. Graphical model of LDA.

(a) draw a vector of topic proportions
$\boldsymbol{\theta}_d \sim Dirichlet(\boldsymbol{\alpha})$
(b) For each word $w_n$ in document d, where $n \in \{1, \ldots, N\}$
 (i) draw a topic assignment
 $\mathbf{z}_n \sim Multinomial(\boldsymbol{\theta}_d)$
 (ii) draw a word $w_n \sim Multinomial\ (\boldsymbol{\beta}_{zn})$

The notation $\boldsymbol{\beta}_t$ is the $V$-dimensional word distribution for topic $t$, and $\boldsymbol{\theta}_d$ is the $K$-dimensional topic proportion for document $d$. The notations $\boldsymbol{\eta}$ and $\boldsymbol{\alpha}$ represent the hyperparameters of the corresponding Dirichlet distributions.

*3.2.1. Predictive Power of Topic Models.* The most typical evaluation of topic models includes measuring how well a model performs when predicting unobserved documents. Specifically, when estimating the probability of unseen held-out documents given a set of training documents, a “good” model should give rise to a higher probability of the held-out documents. Therefore, to measure the predictive power of LDA models with different numbers of topics, we use a metric called perplexity that is conventional in language modeling [24]. Perplexity can be understood as the predicted number of equally likely words for a word position on average and is a monotonically decreasing function of the log-likelihood. Thus, a lower perplexity over a held-out document is equivalent to a higher log-likelihood, which indicates better predictive performance (i.e., lower perplexity score indicates better generalization performance) [22]. Formally, for a test set $D_{\text{test}}$ of $M$ documents, the per-word perplexity is defined as

$$Perplexity(D_{test}) = \exp\left(-\sum_{d=1}^{M} \log p(w_d) \Bigg/ \sum_{d=1}^{M} N_d\right) \tag{1}$$

where $N_d$ is the number of words in document d [22]. In our experiment, we trained a number of LDA models with different number of topics ($k$) and evaluated them against a held-out test set. In particular, we computed the perplexity of a held-out test set to evaluate the models. We held out 20% of the data for test purposes and trained the models on the remaining 80%. Figure 3 shows the predictive power of the models in terms of the held-out per-word perplexity by varying the number of topics. The figure shows that the perplexity decreases with the increase of the number of topics, but tends

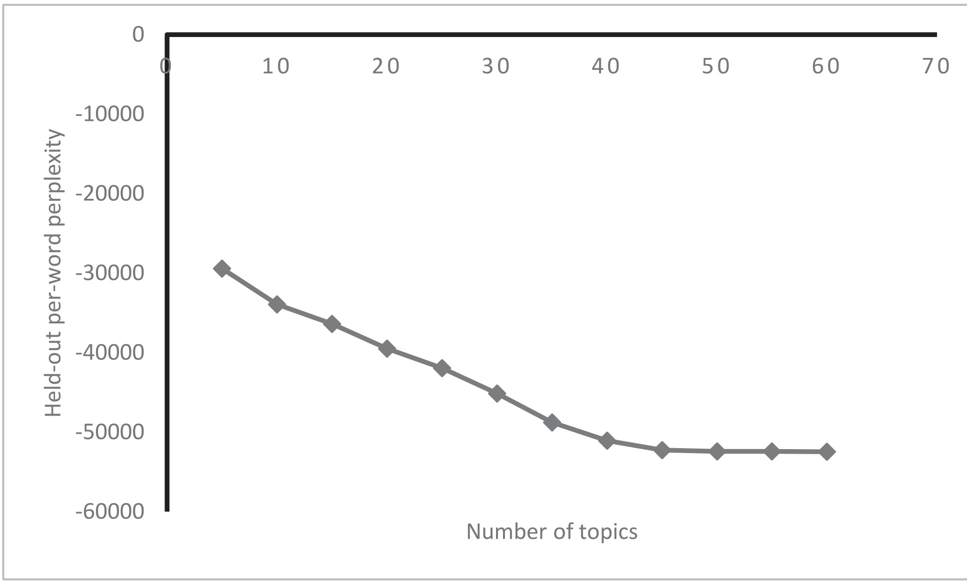


Fig. 3. Held-out per-word perplexity.

to converge to a fixed value eventually. This occurs at around 50 topics, hence we set the number of topics to 50.

*3.2.2. Topics Labeling.* Before using the topics learned via topic modeling to develop design principles, the topics need to be labeled so that we could determine what each topic pertains to. In the literature, topics are usually manually labeled to ensure high labeling quality when such labeling requires domain knowledge [25]. We thus manually labeled the topics learned based on the top 10 words corresponding to each topic. There are a number of user reviews that do not reference a specific design feature but pertain to other aspects of the apps (e.g., "*The app is pricey*", "*This app is well worth the price for me*", etc.). We hence ignored the topics that reflected aspects (e.g., price) irrelevant to the design of the apps. Overall, we were able to assign labels to 32 topics that are related to the design of the apps. Table II presents the 32 topics learned by our LDA model along with the assigned labels. Each topic is visualized using a word cloud, where the font size corresponds to the probability of the word occurring in the topic. To ensure that our labeling was not biased, we asked a doctoral student who has experience in using diabetes self-management apps to independently label the 32 topics. Before the student started tagging, we provided him with the 32 topics labels, which were used as the fixed set of candidate labels. A kappa statistic was then computed between the student's labeling results and ours. The kappa statistic = 0.7239, which indicates substantial agreement between the two sets of tagging results, according to [26]. Therefore, we did not pursue resolving disagreements between our tagging results and those of the student, and our set of labels were then used.

## 4. RESULTS AND DISCUSSION

### 4.1. Design Principles Discovered

The 32 topics obtained from the topic modeling were first mapped to 15 design features, the leaf nodes in Figure 4.

Table II. Topic Labeling Topic1 to Topic 32 are Displayed from Left to Right, Top to Bottom

| | | | |
|---|---|---|---|
| data sync ipad doc iphone help visual written immediately | cloud device graphic sync app transfer potential suppose worth money | Server app upload data ipad support able visit ago work | free server app sync data use lack look develop like |
| *T1: Sync between ipad and iphone* | *T2: Sync with cloud* | *T3: Sync with server* | *T4: Sync with server* |
| convenient meter connect glucose phone app cable book picture fail | pump believe insulin Medtronic dose purchase basal ingredients asset minimum | doctor great data email love app use diabetes easy highly | excel place export endocrinologist data usage respond confuse app product |
| *T5: glucose meter* | *T6: insulin pump* | *T7: Communicating data with doctors* | *T8: Communicating data with doctors* |
| pdf export excel file like data glucometer constant dump harder | support forum group help people site recent progress condition great | track sugar blood carb help glucose use diabetes app control | great allow monitor blood glucose progress level ask share need |
| *T9: Export data* | *T10: Support forum* | *T11:Track blood sugar and carb* | *T12: Track blood glucose and progress* |
| dosage pilot medicine track mmol saver exist obvious bed palm | handy lot informatio n track help sugar program come iphone app | job amazing weekly maintain guy monthly blank health blog register | app food data use log read track great need diabetes |
| *T13: Track medications* | *T14: Track lot of information* | *T15: Tracking* | *T16: Track foods* |
| good app track carb work appreciate bolus like neat feel | calculate figure let appear level everything rock occur software copy | help motivate track plus keep really sure app step daily | graph read nice usable report trend comment icon short tire |
| *T17: Track carb* | *T18: Calculation* | *T19: Tracking* | *T20: Graphs and reports* |

(Continued)

Table II. Continued

| | | | |
|---|---|---|---|
| glance extremely graph trend see thing form flaw easier bg | table bit kept spreadsheet display list value gain edit process | aweso me option allow customize need app thank self output mean | remind watch like feature team lite setup real room app |
| *T21: Graphs* | *T22: Graphs and reports* | *T23: Customization* | *T24: Reminders* |
| ease use great app super comprehensive help beat doctor everything | friendly user monster organ use worth lot app affect little | fun complicated journal ease use straight correctly definitely password app | work great daughte r simple challenge basic app need quantity number |
| *T25: Easy to use* | *T26: User friendly* | *T27: Easy to use* | *T28: Simple app* |
| button navigation shut click aid standard close protein remove method | delete data intuitive twice couple bad mg lost decent non | like scanner barcode stuff adapt age care jot situation minim | bar code scan reader tech like data enjoy recognize dietary |
| *T29: Navigation* | *T30: Data editing* | *T31: Barcode scanner* | *T32: Barcode scanner* |

The mappings between the topics and the design features are often one-to-one. For example, the topics “Sync between iPad and iPhone” was mapped to the design feature “Sync between devices”, the topic “Glucose meter” to the feature “Integration with glucose meter”, and “insulin pump” to “Integration with insulin pump”. There are also some features that correspond to multiple topics. For instance, T20 “Graphs and reports”, T21 “Graphs” and T22 “Graphs and reports” shown in Table II were mapped to the design feature “Graphs and reports”. The design features obtained were then mapped into 11 design principles grouped into four sets as shown in Figure 4. For example, “Sync between devices” and “Sync with cloud” design features were mapped to the “Integration with Information Systems (IS)” design principle, “Integration with glucose meter” and “Integration with insulin pump” were mapped to “Integration with

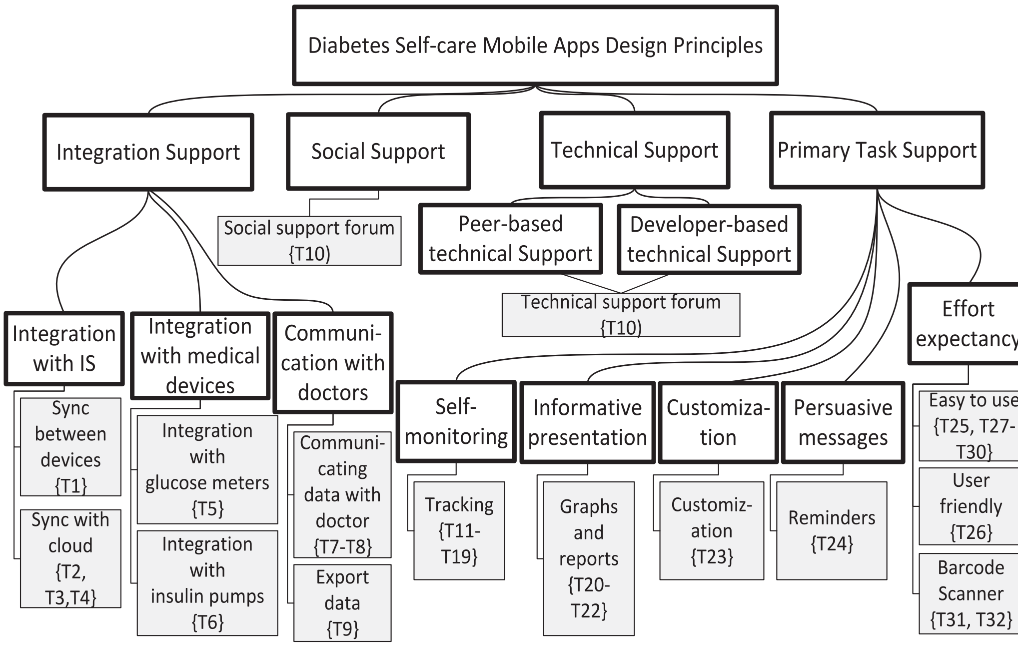


Fig. 4. The structure of the design principles discovered.

Table III. Integration Support Design Principles

| Design Principle | Examples from user feedback |
|---|---|
| **Integration with Information Systems (IS)** Diabetes self-management systems should help users synchronize their data with other systems such as mobile devices, Web servers and the cloud. | - Would be even better if it had the ability to sync across devices.<br>- I can't set it up to synch between my iPad and iPhone apps.<br>- Cannot use iCloud to store data and communicate between devices |
| **Integration with medical devices** Diabetes self-management systems should help users connect with the medical devices in their health environment such as glucose meters and insulin pumps. | - I need it to sync to my meters and pump.<br>- Needs ability to enter pump basal rates.<br>- No support for insulin pumps and basal rates. |
| **Communication with doctors** Diabetes self-management systems should help users communicate their historical data with doctors. | - But unless can back up and send reports to my doctor it has become worthless. |

medical devices", and "Communicating data with doctors" and "Export data" were mapped to "Communication with doctors".

Table III shows the three design principles related to the integration of the apps with other supporting elements in users' context. First, the principle "Integration with Information Systems (IS)" reflects those topics pertaining to synchronization of data between mobile devices and the cloud {T1-T4}. Second, {T5 and T6} represent the design features "Integration with glucose meters" and "Integration with insulin pumps", which were subsequently mapped to "Integration with medical devices". Finally, {T7-T9} related to exporting health-related data into suitable files such as pdf and emailing doctors the data were generalized into the design principle "Communication with doctors".

Table IV. Social Support Design Principle

| Design Principle | Examples from user feedback |
|---|---|
| **Social support**<br>Diabetes self-management systems should help users connect with their peers to share support and motivation to achieve their goals better. | - Very supportive community and educational.<br>- It's nice to have people to talk to that understand exactly what you're going through.<br>- The people on here are so encouraging. |

Table V. Technical Support Design Principles

| Design Principle | Examples from user feedback |
|---|---|
| **Peer-based technical support**<br>The diabetes self-management systems should provide users with peer-based technical support where users can get help from other users when they encounter technical problems with the system. | - The user support forum also has not been working for at least a week. |
| **Developer technical support**<br>The developers of diabetes self-management systems should ensure that there is responsive and sufficient technical support available to the users when they encounter technical problems when using the system [27] | - Sent two emails with questions, no response and yes it has been over a week.<br>- Support is non-responsive.<br>- It appears that app support is non-existent<br>- With NO SUPPORT this app is JUNK. |

To further understand the contextual meaning of "support forum" topic {T10}, we investigated the reviews that are highly associated with this topic. We found that users mentioned two types of support forums, technical vs. social. Hence, we mapped this topic to two design features, "Social support forum" and "Technical support forum," which were then mapped to two design principles "Social support" and "Technical support," as shown in Tables IV and V, respectively. "Social support" indicates that health BCSSs should support building peer-to-peer user communities that enable users to find those with similar health concerns to share experience and provide mutual support. Such support perceived from community members is expected to persuade users to change their health behavior. To this end, it is useful for healthcare mobile apps to build functions such as a social forum, where users can meet and socially support each other.

"Technical support", on the other hand, refers to providing users with adequate technical support when they encounter problems when using the system [27]. Such support can come either from other users (i.e., peer support) via technical support forums or from the system developers (i.e., developers support) who can respond to users' questions.

Table VI shows the five "primary task support" design principles we developed based on users' reviews. These principles support the primary tasks of diabetes self-management, including "Self-monitoring," "Informative presentation," "Effort expectancy," "Persuasive messages," and "customization," each of which corresponds to one or more topics we obtained from LDA.

First, {T11-T19} (see Table II above) are related to tracking all diabetes-related aspects including blood glucose, carb, medication, and progress and were hence mapped to the "Self-monitoring" design principle, which calls for providing means for users to track their performance or status for all health related aspects [8]. Second, {T20-T22} are related to graphs and reports that display data in different formats and were thus mapped to the "Informative presentation" principle, which calls for presenting users' data in an easily readable way and depicting users' improvement trends and historical patterns [28]. Third, T23 was mapped to "Customization", which calls for providing users with customizable options that adapt to the potential needs, interests, personality, usage context, or other factors (e.g., type 1 vs type 2 diabetic) relevant

Table VI. Primary Task Support Design Principles

| Design Principle | Examples from user feedback |
|---|---|
| **Self-Monitoring**<br>Diabetes self-management systems should provide means for users to track their health-related aspects [8] | - The app makes keeping track of glucose levels, carb intake, and medicine I took.<br>- Keep track of my BG and insulin intake.<br>- The app keep track of diabetes related things. |
| **Informative Presentation**<br>Diabetes self-management systems should be able to provide users with readable and informative graphs, reports, and charts of their health-related data, depicting their improvement patterns and historical trends [28] | - The report feature is handy for seeing trends.<br>- I especially like the graphs, where I can see trends and averages over time.<br>- I like the different charts available it makes it easy to see your personal trends. |
| **Customization**<br>Diabetes self-management systems should provide users with customizable options to the potential needs, interests, personality, usage context, or other factors relevant to the users (i.e., type 1 and type 2 diabetic). | - Personalized options such as being able to choose a glucose threshold that the app would use to flag a reading, push notifications, location services, and so on. |
| **Persuasive messages**<br>Diabetes self-management systems should remind users of their target behavior during the use of the app. [8] | - The constant visual reminder really helps keep you on track.<br>- This app is truly helping me, it sends me reminders and is very easy to use.<br>- The reminders keep me on track when I'm busy or just forgetful. |
| **Effort Expectancy**<br>Diabetes self-management systems should reduce effort that users expend with regard to use of the system, e.g., entering their health-related readings. [29] | - Great barcode database and easy to enter foods.<br>- I love the barcode scanner to enter the food.<br>-The app is very easy to use and new data can be entered quickly.<br>- I really like the ease of entering in my readings. |

Table VII. Design Principles in High-Rating Reviews vs. Those in Low Rating Reviews

| Design principle | High rating reviews | Low rating reviews | Significance |
|---|---|---|---|
| Effort expectancy | √ | √ | Essential |
| Self-monitoring | √ | √ | Essential |
| Informative presentation | √ | √ | Essential |
| Communication with doctors | √ | √ | Essential |
| Integration with Information Systems (IS) | | √ | Indispensable |
| Integration with medical devices | | √ | Indispensable |
| Customization | | √ | Indispensable |
| Technical support | | √ | Indispensable |
| Social support | √ | | Enhancing |
| Persuasive messages | √ | | Enhancing |

to the users. Fourth, T24 was mapped to the principle "Persuasive messages", which refers to an app's effectiveness in reminding users of their target behavior [8]. Finally, {T25-T32} are related to ease of use, user-friendly interface, easy navigation and data editing, as well as using a barcode scanner to reduce data input efforts. Thus, these topics were mapped to the "Effort expectancy" design principle, which refers to the degree of ease associated with the use of an app [29].

### 4.2. Design Principles in High Rating Reviews Vs. those in Low Rating Reviews

To further investigate the importance of each design principle, we performed separate topic modeling to identify design principles for top-rated user reviews (i.e., 4- and 5-star reviews) vs. low-rated user reviews (i.e., 1- and 2-star reviews). Table VII shows the design principles discovered in each group and their significance.

As shown in Table VII, the two sets of reviews intersect in four design principles including "Effort expectancy," "Self-monitoring," "Informative presentation," and

"Communication with doctors". Hence, the missing or ineffectiveness of these design principles may lead to users' dissatisfaction (complaining or suggestion behaviors), as shown in a 1-star review: "*As to entering food for carb control it is tedious*" (complaining) and a 4-star review: "It *would be nice if there was an option to scan the bar code of products instead of having to manually enter info if you can't find it in the food list*" (suggestion). At the same time, the presence of these design principles has led to satisfaction and complimenting behaviors in top rated reviews, as shown in a 5-stars review: *"I love the barcode scanner to enter the food"*. Since the missing or ineffectiveness of these design principles has led to dissatisfaction in the low-rated user reviews, and their presence and effectiveness have led to satisfaction in the top rated reviews, we labeled them as the "essential" principles in Table VII.

The two sets of reviews are however disjoint in the remaining design principles. While users in top rated reviews did not report design features related to "Integration with Information Systems (IS)," "Integration with medical devices," "Customization," and "Technical support" design principles, the absence of any of these design principles has led to dissatisfaction (complaining or suggestion behaviors) in the corresponding low-rated reviews. Thus, we labeled these design principles as "indispensable" in Table VII.

Design principles such as "Social support" and "Persuasive messages" were mentioned in the top-rated reviews but not in the low-rated reviews. Whereas the absence of these design principles might not have been noticed and did not lead to complaints in the low-rated reviews, their presence or absence has led to compliments or suggestions in the high-rated reviews as shown in the following examples: "*Being a diabetic and having a platform to quickly connect and share with others who have this rotten disease makes the struggle to regain your health easier*", and "*A reminder feature would be a nice enhancement*". The absence of these design principles did not directly result in complaints in low-rated user reviews, but their presence seems to enhance user satisfaction as shown in top-rated reviews. We hence labeled them as "enhancing" in Table VII.

### 4.3. Comparison with Pertinent Literature

We compared our design principles proposed above with those reported in related literature as shown in Table VIII.

First, we compared our research with the persuasive systems design principles encompassed in the Persuasive Systems Design (PSD) model developed by Oinas-Kukkonen and Harjumaa [8]. Five of the design principles in the PSD model overlap with our design principles. The *reduction* principle in the PSD model (i.e., "system should reduce the effort that users expend with regard to performing their target behavior") corresponds to the principle "Effort expectancy" in our study. Both the PSD model and our study contain the principle "Self-monitoring". The *tailoring* principle in the PSD model corresponds to our "Customization" principle, and *reminders* in the PSD model to "Persuasive messages" in our research. Finally, the "Social support" principle exists in both studies. Grounding these principles in users' feedback helps provide empirical support and further demonstrates the importance of these design principles for self-care mobile systems. Moreover, our research identified several design principles including "Informative presentation", "Integration support" (including integration with IS, integration with medical devices, and communication with doctors), and "Technical support" that are not included in the PSD model. These design principles are essential for mobile health apps. For instance, the "Informative presentation" principle (i.e., depicting users' improvement patterns and historical trends using graphs and reports) is expected to improve the persuasiveness of health BCSSs through nudging users toward healthy behaviors.

We also compared our findings with the literature related to health BCSSs acceptance and the acceptance of telehealth systems. The "Technical support" design principle,

Table VIII. Comparison with Existing Literature

| | Primary task support | | | | | Integration support | | | Social | Technical |
|---|---|---|---|---|---|---|---|---|---|---|
| **Study** | **Self-Monitoring** | **Informative Presentation** | **Effort Expectancy** | **Persuasive messages** | **Customization** | **Integration with IS** | **Integration with medical devices** | **Communication with doctors** | **Social support** | **Technical support** |
| **Design principles developed by Oinas-Kukkonen and Harjumaa(2009)** | | | | | | | | | | |
| Oinas-Kukkonen and Harjumaa [8] | * | | * | * | * | | | | * | |
| **Literature of Consumer health information technology (CHIT) acceptance** | | | | | | | | | | |
| Or et al. [30] | | | * | | | | | | | |
| Lehto et al. [31] | * | | | * | | | | | | |
| Ruland et al. [32] | | | | | | | | | * | |
| Karppinen et al. [33] | | | * | | | | | | | * Technological issues |
| **Technology acceptance for elderly patients/Telehealth systems** | | | | | | | | | | |
| Singh et al. [27] | | | * | * | | | | | * | * |
| Cimperman et al.[34] | | | * | | | | | | * | * |
| Peek et al. [35] | | | | | | | | | * | |

which is largely ignored in the literature that focuses on developing design principles for BCSSs, is supported in the literature related to user acceptance since technological support, or the lack of thereof, directly facilitates or impedes the actual use of these systems, particularly for novice users. The results also revealed that the "Informative presentation," "Customization," and "integration support" design principles are missing in the user acceptance studies.

### 4.4. Relationship between Design Principles and User Ratings: Empirical Analyses

To evaluate the significance of the design principles we identified, we investigated the relationship between the design principles and user ratings. We first examined the relationship between the design principles and users' complaints (i.e., 1- or 2-star reviews) in Section 4.4.1. We then performed another empirical study to prove the relationship between the number of design principles incorporated in apps and user ratings in Section 4.4.2

*4.4.1. Relationship to Users' Complaints.* We focused on users' complaints contained in 1- or 2-star reviews since, in comparison with the high-rated reviews, these low-rated reviews are more likely to reflect users' concerns and shed light on design principles that should be considered but unfortunately have been ignored in the current research and practice. We first considered the frequency of occurrences of each principle in the complaints. Showing that one design principle has been frequently mentioned in the complaints provides evidence of the importance of that design principle. As discussed in Section 4.1, we mapped the topics extracted using LDA to a set of design principles, each of which is pertinent to one or more design features. Hence, instead of directly counting

Table IX. The Most Frequent and Impactful Design Principles in Users' Complaints

| | Most Frequent | | Most Impactful | |
|---|---|---|---|---|
| Design principle | Rank | Percentage(%) | Rank | 1:2 star* |
| **Effort expectancy** | **1** | **18.2** | **3** | **1.7** |
| Easy to use | | 15.0 | | 2.7 |
| User friendly | | 2.2 | | 0.6 |
| Barcode scanner | | 1 | | 0.7 |
| **Integration with Information Systems (IS)** | **2** | **16.2** | **2** | **2.0** |
| Sync with cloud | | 12.0 | | 2.5 |
| Sync between devices | | 4.2 | | 1.1 |
| **Self-monitoring** | **3** | **10.0** | **8** | **0.7** |
| Tracking | | 10.0 | | 0.7 |
| **Informative presentation** | **4** | **9.2** | **6** | **1.2** |
| Graphs and reports | | 9.2 | | 1.2 |
| **Technical support** | **5** | **8.4** | **1** | **3.7** |
| Technical support forum | | 8.4 | | 3.7 |
| **Customization** | **6** | **7.8** | **4** | **1.6** |
| Customization | | 7.8 | | 1.6 |
| **Communication with doctors** | **7** | **6.6** | **5** | **1.5** |
| Export data | | 3.8 | | 1.4 |
| Communicating data with doctors | | 2.8 | | 1.8 |
| **Integration with medical devices** | **8** | **4.8** | **2** | **2.0** |
| Integration with glucose meter | | 4.2 | | 2 |
| Integration with insulin pump | | 0.6 | | 2 |
| **Persuasive messages** | **9** | **0.4** | **7** | **1** |
| Reminders | | 0.4 | | 1 |
| **Social support** | **10** | **-** | **9** | **-** |
| Social support forum | | - | | |
| **Total** | | **81.6** | | |

*: The ratio of 1 to 2-star ratings for each design principle. For example, a 1 to 2-star ratio of 2 for a design principle indicates that this design principle has 2 times as many 1-star ratings as 2-star ratings.

the frequency of the design principles, we first mapped the complaints contained in 1- and 2-star reviews to the design features. We noticed that in one review, users could complain about multiple features; hence, we split such a review into multiple complaints, each of which pertains to just one feature. We also ignored the reviews irrelevant to the design of the apps and labeled the complaints that are generic and cannot be mapped to a specific design feature (e.g., "*Not that good. Used much better ones"*) as "others". In total, we tagged 500 complaints out of 526 one- and two-star reviews. To ensure that our tagging was not biased, we provided a graduate student with the set of design features we identified previously and asked the student to independently tag the complaints. The kappa statistic computed based on ours and the student's tagging results was 0.7559, which indicates substantial agreement between the two sets of tagging results [26]. After finishing tagging the reviews, we counted the frequency of each design feature in the complaints, and then, by summing up the frequency of the design features belonging to each design principle, we obtained the frequency of each design principle mentioned in the complaints. The "most frequent" column of Table IX shows the rank and the frequency in percentage of each design principle and its associated design features.

As shown in Table IX, the principle "Effort expectancy" occurred in 18.2% of the complaints, "Integration with Information systems (IS)" in 16.2%, "Self-monitoring" in 10%,"Informative presentation" in 9.2%, "Technical support" in 8.4%, "Customization" in 7.8%, "Communication with doctors" in 6.6% and "Integration with medical devices" in 4.8%. Together, these eight design principles appeared in more than 80%

of all the complaints. “Effort expectancy” is the most frequently mentioned principle in the complaints. According to the principle, diabetes mobile apps should be designed to provide ease of use. For example, a barcode scanner could significantly reduce data input overhead. The results shown in Table IX also highlight the importance of the three design principles related to integration (including “Integration with IS,” “Communication with doctors,” and “Integration with medical devices”), which appeared in more than 25% of all the complaints. These integration-related design principles are critical for mobile apps but have been largely ignored in the extant literature. Among the three principles, special attention should be paid to “Integration with Information systems (IS)”, which ranked the second in frequency among all the principles. Many users demanded the integration and synchronization of the mobile diabetes apps with other IS components. For instance, one user complaint reads: *“The app does not synch data between iPhone and iPad version of the app”*. Another reads: *“No sync’ing to the cloud”*. Our findings also indicated the importance of “Self-monitoring”, which means that mobile diabetes apps should provide functions that enable users to track a comprehensive list of health-related aspects. For instance, one user complained: *“I am a type 2 diabetic, use a slow and fast acting insulin as well as two different oral meds. This app does not have a way to track this”*. We also found that “Informative presentation” is frequently mentioned in the complaints, which demonstrates that it is important to use graphs and reports to depict users’ improvement patterns and trends. For instance, one user complained that *“it would be nice if app would display graphs of blood sugars, carbs, mealtimes, as well as insulin doses”*.

We found that the principles that have been the least frequently mentioned in user complaints include “Persuasive messages” and “Social support”. In particular, “Social support” has not been mentioned in any of the complaints. A further investigation of the 30 diabetes apps revealed that only one of them, Diabetic Connect,[2] mentioned a “social forum” in its product description. While users did not complain of the lack of social support in other applications, the existence of the social forum in Diabetic Connect has brought about users’ praises. For instance, in a 5-stars review, a user applauded the social forum: “Being a diabetic and having a platform to quickly connect and share with others who have this rotten disease makes the struggle to regain your health easier”. Our findings are consistent with the existing research such as Chomutare et al. [18] that pointed out that social network functions such as social forums are largely missing in current mobile health apps. In order to enhance the design of health apps, it is critical for practitioners to take a holistic socio-technical approach and focus on not only the technical issues but also the social aspects of the apps.

Next, we ranked the design principles with respect to their impact on users’ negative ratings (see the “most impactful” column in Table IX). Analyzing the impact of the design principles on the user ratings adds another dimension for analyzing the importance of the different design principles. While a design principle $A$ may be more frequently mentioned in the complaints than another principle $B$, users may be less concerned about $A$ and give higher ratings (in this context, 2-stars ratings rather than 1-star ratings). Principle $B$, on the other hand, may appear less frequent than $A$ in the complaints, but the lack of the principle could be more negatively perceived and lead to 1-star ratings.

Drawing upon the method proposed by Khalid et al. [36], we determined the impact of each design principle by computing the ratio of 1- to 2-star ratings for the principle. For example, a 1- to 2-star ratio of 2 for a design principle indicates that this design principle appeared in twice as many 1-star ratings as 2-stars ratings. Columns 4 and 5 of Table IX show the rank and the 1:2 star ratio for each design principle and its

[2]https://itunes.apple.com/us/app/diabetic-connect/id418076239?mt=8.

Table X. Descriptive Statistics of Variables for Econometric Analysis

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| DesignPrinciplesCount | 5.33 | 1.54 | 1 | 7 |
| ReviewsNumber | 140.6 | 116 | 50 | 450 |
| AppPrice ($) | 2.73 | 5.09 | 0 | 24.99 |

associated design features. It turned out that the most negatively perceived design principles were different from the most frequently mentioned principles. Observing the results in Table IX, we noticed that the problems related to the principle “Technical support” were the most negatively perceived by the users. Also, we noticed that the frequency and impact of this principle diverged in terms of the rank. While “Technical support” was only fifth in frequency, it ranked the first in impact. This demonstrates that the principle “Technical support”, which has been largely missed in the existing research, has a significant impact on user ratings, though it is less frequently mentioned in the complaints than some other principles.

“Integration with information systems (IS)” and “Integration with medical devices” tied for the second rank in impact. Again, these two design principles have been largely ignored in the existing research. In particular, “Integration with IS” achieved high ranks in both impact and frequency. This indicated that in the era of the Internet of Things, supporting mobile health apps with cloud computing and integrating them with medical devices (such as insulin pumps in the context of diabetes apps) have become an essential requirement for the design of mobile health apps. “Effort expectancy” ranked the third in impact. Particularly, many users were frustrated when the apps entailed significant efforts for data entry and when it was difficult to update the readings in some of the apps. It was followed by “Customization,” “Informative presentation,”and “Persuasive messages” in the ranking of impact. Finally, our findings show that users were the least concerned about the issues related to “Self-monitoring”.

*4.4.2. Relationship between Number of Design Principles and User Ratings.* In this section, we conducted another empirical study to explore the relationship between the number of design principles implemented in an app and its user ratings. We intended to test the following hypothesis: *Apps that have implemented more design principles tend to have higher user ratings*.

We counted a design principle as being effectively implemented in the app if there are more positive reviews related to that design principle than negative ones. However, when analyzing the reviews, we noticed that some design principles were little mentioned in the user reviews. For instance, the comments related to “Social support” have been found only in one app (i.e., Diabetic Connect). In such situations, we looked at the description of the app to confirm if the design principle has been implemented in the app. We considered a design principle missing in an app if neither did users mention it in the reviews of the app, nor did we find contents related to the principle in the description of the app.

In order to test our hypothesis, we ran an OLS linear regression model with the average user ratings of an app (i.e., the variable UserRate) as the dependent variable and the number of design principles effectively implemented in the app (i.e., the variable DesignPrinciplesCount) as the independent variable. We also controlled for the confounding factors including (1) the number of reviews for each app (i.e., the variable ReviewsNumber) and (2) the price of each app (i.e., the variable AppPrice). The descriptive statistics of the independent variable and the control variables are shown in Table X. A diabetes application has a mean of 140.6 reviews. On average, 5.33 of the 11 design principles have been effectively implemented (with more positive reviews than negative reviews) in an app.

Table XI. Correlation for the Variables

| | DesignPrinciplesCount | ReviewsNumber | AppPrice |
|---|---|---|---|
| DesignPrinciplesCount | **1.00000** | **0.26310** | **0.38154** |
| ReviewsNumber | | **1.00000** | **0.05874** |
| AppPrice | | | **1.00000** |

Table XII. Estimation Results

| Variable | Parameter estimate | Standard Error | *P*-value |
|---|---|---|---|
| Intercept | 2.28635 | 0.25243 | <0.0001*** |
| DesignPrinciplesCount | 0.39464 | 0.05999 | <0.0001*** |
| ReviewsNumber | 0.00030575 | 0.00069849 | 0.6652 |
| AppPrice | −0.02775 | 0.01753 | 0.1255 |
| Number of observations | 30 | | |
| R-square | 0.6557 | | |
| Adj R-square | 0.6160 | | |

The dependent variable is UserRate. Robust standard errors are listed in parenthesis; *** denote significance at .01.

Table XI shows the Pearson correlations between the variables. We observed that the number of design principles is positively correlated with the number of reviews, which indicates that the apps that implemented more design principles could attract more users and have more user reviews. The number of design principles is also positively correlated with the price of the app, which means that overall, the high-priced apps tend to implement more design principles than the low-priced or free ones. The correlations between the variables are moderate. Hence, there is absence of multicollinearity between the predictors in a regression model.

We ran the following regression model:

$$\mathrm{UserRate}_i = \alpha_i + \beta_1 \,.\, \mathrm{DesignPrinciplesCount} + \beta_2 \,.\, \mathrm{ReviewsNumber} + \beta_3 \,.\, \mathrm{AppPrice} + \varepsilon_i$$

We found a significant positive effect of the number of design principles (i.e., DesignPrinciplesCount) on the user ratings of the app (see Table XII), thus supporting the hypothesis that apps that have implemented more design principles tend to have higher user ratings. While the impact of the other two variables (including ReviewsNumber and AppPrice) on user ratings is statistically insignificant, the OLS regression results in an R2 of 0.6557, suggesting the predictive power of the number of design principles for user ratings.

## 5. CONCLUDING REMARKS

This study aims to discover design principles of smartphone health behavioral change support systems (BCSSs) by analyzing the actual use of these systems. We adopt a text-mining-based approach to leveraging online user reviews as a primary data source. Given the importance of diabetes self-management applications for improving the lives of diabetes patients by leveraging patients' self-care practices, we use mobile applications for diabetes self-management as a problem domain. To demonstrate the importance of the design principles discovered, we manually calculate the frequency of each design principle in low-rated users' reviews (i.e., users' complaints). The findings revealed that the design principles underlie more than 80% of the users' complaints. We also compare the design principles we discovered with the widely used existing persuasive design principles presented in [8] as well as the existing literature regarding consumer health information technology (CHIT) acceptance and technology acceptance of Telehealth systems.

The findings of our research reveal that some design principles are more important than others. "Effort expectancy," "Self-monitoring," "Informative presentation," "Communication with doctors," and "Integration with Information Systems (IS)" are the most important principles. They are followed by "Integration with medical devices," "Customization," and "Technical support" that are also critical. "Social support" and "Persuasive messages" are the least important ones according to the user reviews. Moreover, our findings indicate that users are the most bothered by issues related to the following design principles: "Technical support," "Integration with Information systems (IS)," "Integration with medical devices," "Effort expectancy," "Customization," and "Communication with doctors," We also found the significant positive impact of the number of design principles implemented in an app on the app's user ratings.

The findings indicate that the current practice in developing self-care apps stresses a techno-centric approach, focusing primarily on the technical aspects, while treating social and structural design features (such as integration of the apps with other IS components) as secondary and complementary rather than integral to an application. In essence, the design of health apps should connect patients with peers, with whom they can exchange social support and experience, cooperate, and compare their performance. Such connection has significant importance in persuading users to change their behavior and achieve their goals as they are more likely to perform when they perceive social support and observe others' performance. It is thus paramount to view diabetes self-management apps as a component within a holistic health system. In this system, the app should enable patients to export and communicate their readings and information with physicians, and it should be integrated with other health apps (i.e., fitness apps), medical devices such as glucose meters and insulin pumps, and other information systems such as mobile devices and servers. Further, our findings confirmed the importance of personalization [37], which means that developers of mobile health apps are highly recommended to allow users to choose and customize how data is displayed, what metrics are being measured, and what are the optimal levels for these metrics. Organizationally or operationally, the findings of this study also present the technical support as an important acceptance factor for these consumer health systems.

Theoretically, this work contributes to the existing knowledge base of persuasive systems design by (1) supporting some existing theoretical design principles developed by Oinas-Kukkonen and Harjumaa [8] and (2) inferring new design principles. Methodologically, this study exploits users' feedback in form of online reviews. In essence, the design of persuasive systems requires understanding of user context, recognizing the intent, event, and strategies for the use of a persuasive system [8]. In this regard, user involvement is key in persuasive systems design, which can help shift the focus of innovation from pure technology to the context of daily life [38]. We hence developed design principles based on users' reviews. Extracting insights from users' reviews particularly pertains to persuasive systems where the intrinsic objective is to persuade users to possibly do things they would otherwise not do or not have an immediate incentive to do, which often leads to the sensitivity and criticality of users' feedback and input. The approach could also be generalized to other systems that share some of these characteristics, such as educational games that are designed to help users learn about certain subjects and persuade them to learning.

Instead of manually analyzing and coding the reviews, which is time-consuming and subjective, we used text mining, more specifically the LDA algorithm for topic modeling, to automatically extract design features from large amounts of text data. This automatic approach to knowledge extraction has implications for practice that can help mobile app developers develop more successful diabetes apps that promote user self-efficacy and sustainable use. Since self-care application developers face pressure to continuously refine the quality and value of their apps to meet evolving user expectations and sustain sales, a means of informing these refinements can be through the practice of the proposed method that automatically harvest insights from user reviews, which help developers measure adoption and monitor performance of their current apps as well as competing apps.

Limitations of this research are first related to the generalizability of our design principles. In future research, we aim to use the proposed method in other application domains than diabetes and further explore the generalizability of the proposed principles for persuasive systems design. We will also further investigate the evaluation methods for topic modeling. Indeed, it is still a challenge to evaluate the results of topic modeling as unsupervised technique for exploratory analysis that is used to discover patterns in textual data. It is still an open question for designing robust evaluation methods so that the user could trust the topics describing text that he or she has never read.

## APPENDIX A. PREVIOUS EMPIRICAL RESEARCH RELATED TO ONLINE REVIEWS

| Author(s) | Research Context and method | Chief purposes | Major findings |
|---|---|---|---|
| [11] | • Book data from Amazon.com and Barnesandnoble.com.<br>• Regression. | • To examine the effect of consumer reviews on relative sales of books. | • An improvement in a book's reviews leads to an increase in relative sales at that site.<br>• The impact of one-star reviews is greater than the impact of five-star reviews. |
| [39] | • A panel data set of three products categories (audio and video players, digital cameras, and DVDs).<br>• Econometric, text mining, and predictive modeling techniques. | • To examine the impact of reviews on economic outcomes like product sales. | • The extent of subjectivity, informativeness, readability, and linguistic correctness in reviews matters in influencing sales and perceived usefulness. |
| [40] | • Ventures information from VentureXpert database and the blog coverage data from Google Blogsearch.<br>• Econometric analysis. | • To investigate the effect of eWOM on venture capital financing. | • The impact of negative eWOM is greater than the impact of positive eWOM and that the effect of eWOM on financing decreases with the progress through the financing stages.<br>• The eWOM of popular bloggers helps ventures in getting higher funding amounts and valuations. |
| [41] | • Qualitative user-marketer interaction content data from a fan page brand community on Facebook and consumer transactions data.<br>• Text mining and econometric modeling | • To explore the impact of user-generated content (UGC), and marketer-generated content (MGC), on consumers' apparel purchase expenditures. | • Social media contents have impacts on consumer purchase behavior through embedded information and persuasion.<br>• User-generated content (UGC) exhibits a stronger impact than marketer-generated content (MGC) on consumer purchase behavior. |

| Author(s) | Research Context and method | Chief purposes | Major findings |
|---|---|---|---|
| [42] | • Digital camera dataset from Amazon.com.<br>• Network analysis and text sentiment mining techniques | • Integrating network analysis with text sentiment mining techniques to propose product comparison networks as a novel construct, computed from consumer product reviews. | • WOM in social media constitutes a competitive landscape for firms to understand and manipulate. |
| [43] | • A panel of book dataset from Amazon.com.<br>• Multiple equation model. | • What is the differential impact of sentiments and ratings on sales? | • Sentiments have a direct significant impact on sales.<br>• Ratings do not have a significant direct impact on sales but have an indirect impact through sentiments |
| [44] | • Seventy-nine paid and seventy free apps from an iOS app store.<br>• Sentiments and econometric analysis. | • To examine the effect of textual consumer reviews on the sales of mobile apps. | • Consumers' comments on service quality have a stronger unit effect on sales rankings than comments regarding product quality. |
| [12] | • Quasi-experimental design (capture the real patterns of online reviews in e-Commerce) and online questionnaires. | • To examine the effect of social consensus in product reviews, represented by review balance and volume, on online shoppers' risk perception, uncertainty, attitude and subsequent purchase intention. | • By impacting buyers' risk perception and shaping their attitude, online reviews, especially negatively distributed reviews, play important role in determining buyers' purchase intention. |
| [45] | • Online user reviews for hotels.<br>• Sentiment and econometric analysis | • To examine the impact of online user reviews on users' overall evaluation and content-generating behavior | • Different dimensions of user reviews have significantly different influences in shaping user evaluation and driving content generation. |
| [46] | • Online reviews for hotels located in 16 countries.<br>• Latent dirichlet analysis (LDA) | • Identify the key dimensions of customer service voiced by hotel visitors using a data mining approach. | • LDA discovers 19 controllable dimensions that are key for hotels to manage their interactions with visitors. |

## APPENDIX B. DIABETES APPLICATIONS

| App Name | Category |
|---|---|
| Diabetes App - Blood sugar control, glucose tracker and carb counter | Medical |
| Glucose Buddy - Diabetes logbook manager w/syncing, blood pressure, weight tracking | Medical |
| Diabetes Tracker with Blood Glucose/Carb Log by MyNetDiary | Medical |
| Diabetes App Lite - Blood sugar control, glucose tracker and carb counter | Medical |
| Diabetes in Check: Coach, blood glucose, and carb tracker | Medical |
| Diabetes Log | Health & Fitness |
| Track3 - Diabetes planner, diabetes glucose logbook, diabetes tracker, carb counter | Medical |
| Glucose Companion Free | Medical |
| Blood Sugar Diabetes Control | Health & Fitness |
| Diabetik | Medical |
| Healthsome G for Glucose | Medical |
| WaveSense Diabetes Manager | Health & Fitness |
| Glucose Companion by Maxwell Software | Medical |
| LogFrog DB Lite - A leap in diabetes management | Health & Fitness |
| iBGStar® Diabetes Manager | Medical |
| Diabetes Pedometer with Glucose & Food Diary, Weight Tracker, Blood Pressure Log and Medication Reminder by Pacer | Medical |
| Diabetes Pilot Classic | Health & Fitness |
| Diabetes Pal App - Logbook manager for blood glucose, A1c, nutrition, medication, weight, blood pressure analysis + withings and BodyMedia | Medical |
| LogFrog DB - A leap in diabetes management | Health & Fitness |
| Diabetes in Pregnancy - Gestational diabetes logbook and manager | Medical |
| Diamedic | Health & Fitness |
| BGluMon - Blood glucose monitor | Medical |
| Diabetes - DailyDiab | Medical |
| Diabetes Logbook by mySugr | Medical |
| Glucose Buddy Pro - Diabetes managing logbook w/blood pressure and weight Tracking | Medical |
| Glooko | Medical |
| Glucose-Charter | Medical |
| Diabetic Connect | Social networking |
| Health Tracker & Manager for iPhone | Health & Fitness |
| myMedtronic Connect | Health & Fitness |

## ACKNOWLEDGMENTS

The authors would like to thank the associate editor and the reviewers for their valuable and constructive comments during the review process. We also acknowledge valuable feedback from the reviewers of the Twenty-Fifth Workshop on Information Technologies and Systems (WITS 2015).

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Received June 2016; revised November 2016; accepted February 2017