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EHR: a Sensing Technology Readiness Model for Lifestyle Changes

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Abstract Interest in developing user-centered sensing technologies for personalized behavior change has gained significant momentum. However, very little research work has been done to understand issues relative to user readiness and adoption of the sensing technologies to change their behaviors, especially the motivations as well as the concerns and impediments for adoption. We have developed a model called EHR (e-health readiness), to understand and explain the relationship between user habits, perceived healthiness and beliefs towards sensing technologies, and how these factors influence user readiness to use sensing technologies to manage their wellness. We then validate the model using psychometric methods by a large-scale user study (N = 541). Results show overall readiness to sensing technologies is positively influenced by readiness to monitor health conditions, share data within social networks, and receive recommendations. Additionally, readiness is significantly impacted by perceptions of healthiness, technology satisfaction and usefulness of such technology. Finally, we summarize user motivations and concerns for pervasive sensing tools through qualitative analysis on their comments. We present this model and the results of this survey to shed light on designing future sensing technologies for behavior change.

Keywords Sensors · Pervasive health · Technology readiness · User modeling

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1 Introduction

Citizens of the industrialized nations suffer from obesity and stress due to long working hours, inactivity and highly competitive lifestyle. An unhealthy lifestyle is also the cause of long-term diseases such as depression, cardiovascular diseases, and cancer. Researchers are seeking technology innovations to motivate daily behavioral changes towards a paradigm shift from healthcare to preventive care, for example, by encouraging doing more physical exercises, having a healthier diet, sleep, and a more active social life with family and friends.

Nowadays, there is an increasing interest for developing effective user-centered sensing technologies for personalized lifestyle changes [1–4]. However, being ready for technology for lifestyle change is a complex process involving sensitive issues such as the fear of being monitored, the reluctance of receiving recommendations from a device, and privacy concerns [5]. Evaluating a technology's contribution to lifestyle and behavior change and users' acceptance after usage requires large studies and significant resources [5]. As a first step, we are interested in understanding what types of users are likely to accept these tools and what influences their readiness prior to exposure to such tools. By readiness, we refer to whether users are willing to use and make favorable responses to the technologies.

Our research was inspired by findings from behavioral and medical studies that users' health habits significantly influence their perceived health [6] and that perceived health has a determining effect on their attitudes towards various aspects of tools for healthcare and overall readiness for such tools [7]. Currently, sensing technologies for preventative healthcare mainly use means that help users to 1) reflect on their health conditions, 2) share data within social networks, and 3) receive recommendations [4]. We aim to investigate how health habits influence user readiness for the above aspects. More concretely, we are interested in the following research questions:

- Can we infer users' readiness for using sensing technologies for self-reflection, social sharing and receiving recommendations from users' health habits and perceived health?
- How does users' readiness for using sensing technologies to reflect on their health, share health related data and receiving recommendations influence their overall readiness for technology for lifestyle changes?

To answer these questions, we hypothesized a model called EHR (e-health readiness) that presents the human factors that determine the willingness of laypersons – non-professional and non-patients – to self-reflect, share and receive recommendations of health data before they use technologies for lifestyle change. We then validated it using factor analysis and structural equation modeling (SEM) through an online user study. The main contribution of the research is to understand the mechanisms underlying user readiness for sensing technologies for personal healthcare and provide practical suggestions to design more effective pervasive and preventative healthcare systems.

2 Related work

2.1 Sensing technology for behavior change

Behavior change is a complex process and using technology for behavior change adds another layer of complexity. Technological interventions for behavior change should handle both psychological and technical barriers as well as seeking ways to make it easier to adopt. Klasnja et al. [8] mentioned that before jumping to system evaluation, as it is usually done in clinical studies, problems regarding the design of the technology should be resolved at the early stages in order to ensure that design problems are not diminishing the usefulness of the system. This can be achieved by an in-depth understanding of the field by surveying the related literature in the well-being domain, obtaining consultation from experts and by conducting ethnographic studies with users. We will first give a survey of existing sensing technologies that monitor people's well-being related activities and that recommend behavior change strategies. Following that we will mention previous work that discusses the barriers to behavior change and adoption of technology for well-being.

Applications for lifestyle changes focus on four main different areas: physical activities, sleep, emotional well-being, and diet. One of the early attempts to promote physical activity is Fish'n'Steps [9]. It is a social computer game that links a player's daily foot step count on a pedometer to the growth of animated virtual fish in a fish tank. The results emphasized the importance of positive reinforcement in long-term behavioral change. UbiFit garden [10] is composed of a small device attached to the hip consisting of various sensors to infer activities such as walking, running, climbing stairs and an application that allows the users to set goals and monitor their achievements. BeWell [11] infers users' physical activeness, sleep quality and social activeness using sensor data on smartphones (e.g., accelerometers and microphones) as well as phone-recharging behavior. AffectAura [12] deploys a multi-sensory setup to obtain audio, video, physiological and contextual data and predict emotions using a dimensional model of arousal, valence and engagement. The research is based on the fact that automatically annotated life-logs with users' affective states can increase emotional awareness and enhance mental health. The effectiveness of these systems was evaluated based on interviews and surveys conducted with participants.

Researchers nowadays discuss the appropriate design strategies for lifestyle changes following a theory-driven approach [15] adopted from behavioral science and social psychology such as Transtheoretical Model of Behavior Change and Goal Setting Theory. They have also developed new health intervention models, persuasion strategies as well as design guidelines [16]. For example, eight design guidelines have been defined for lifestyle change technologies such as data abstraction, unobtrusiveness and aesthetics and the guidelines were applied in the design of UbiFit system [15]. Another line of research conducted ethnographic studies with users in order to understand their concerns and needs about using technology for lifestyle change. Toscos et al. [17] discussed about the barriers to physical activities based on a qualitative analysis of message board traffic from a three-month lifestyle intervention that aimed to promote physical activity and healthy diet. Top barriers reported in their study include "illness or injury", "lack of motivation" and "lack of time." They proposed several design strategies such as setting realistic expectations, providing alternative exercise recommendations (e.g. disease-specific, fun activity) and creating personal connections using personalized health messages. Choe et al. [18] interviewed sleep experts and used online surveys to understand factors such as stress and room temperature that impact sleep quality. Totter et al. [19] developed a human-centered design and evaluation framework for wearable sensors based on interviews with 16 users and survey with 64 users from three different countries covering aspects such as sensor efficiency and reliability (e.g. quality of use over time), wearability (e.g. daily and sleep comfort) as well as medical (e.g. hygiene, skin comfort) and affective aspects (e.g. social acceptance, look and feel).

To our knowledge, efforts so far for understanding user concerns and needs regarding sensing technologies for lifestyle change is based on small-scale analysis and evaluation of user behaviors on a single aspect of well-being. Yet, it is not clear how a large segment of users are ready for this kind of technology in an integrated framework of well-being dimensions. Most importantly, very little research work has been done to understand in-depth the types of users who are more predisposed to adopt technology and their motivations and concerns. It is mainly due to the fact that, so far some of the technologies have not become mature enough and still cannot go out of the labs to the streets and even people are not aware of the existence of such technology. However, in parallel it is crucial to understand the trends in the society towards sensing technologies for lifestyle changes and whether people are ready to accept it. The work closest to our goals is conducted by Cherubini et al. which investigates the barriers in the adoption of today's mobile phone contextual services [20]. Some of the barriers they mention include trust, privacy, personalization and popularity. Although their work is not in the area of lifestyle changes, similar large-scale studies need to be conducted in order to understand the concerns of users about the adoption of such sensing technologies. We will also leverage our know-how in our previous work on understanding the user issues in recommender systems [21]. In the following sections, we will present our results towards this goal.

2.2 Evaluating technology acceptance for healthcare

Researchers have proposed and validated models to evaluate consumer adoption for healthcare systems [22] based on Technology Acceptance Model (TAM) [23]. TAM indicates that user perceived usefulness (PU) and perceived ease of use (PEOU) of a system could positively influence their attitudes towards the system, which then predicts their future usage intention. For example, Wu et al. [24] developed a model based on TAM to evaluate healthcare professionals' usage intention of mobile healthcare systems (MHSs). They validated the model using survey results collected from physicians, nurses, and medical technicians who were currently using various MHSs. They found that both users' current technical background and perceived ability to use the system significantly predict PU and PEOU. In a slightly different context, the Almere model [12] explains acceptance of assistive social robots for elderly care. The model also addresses the social aspects of a system in predicting user acceptance, such as perceived social presence and perceived sociability. Both models target at assessing user attitudes and behavioral intentions after using certain healthcare systems.

Researchers also consider the role of human factors before users deploy technologies [13, 14]. In the field of technologies for healthcare, in particular, Steele et al. [25] investigated elderly persons' attitudes and acceptance of using wireless sensor networks to assist healthcare They identified crucial elements that influence acceptance by conducting a focus-group study and showing participants a sample device. Sensor Acceptance Model (SAM) [26] consists of two questionnaires, assessing patients' attitudes before and after using sensor technologies respectively. The pre-study questionnaire (Q1) evaluates patients' physical health, mental health and their expectation for the sensors. Post-study questionnaire (Q2) evaluates patients' attitude towards different dimensions of sensors, such as hygienic aspects, skin reactions and etc. In this model, physical health, mental health and expectations in Q1 influence patients' perception on various dimensions of sensors in Q2 and hence predict sensor acceptance index in Q2.

The above work evaluates technologies designed for specific user groups, such as patients, elderly people and healthcare professionals. The technologies considered are designed for their respective needs. For example, elderly people have strong demand for staying independent with the help of technology [27]. Healthcare professionals possess deeper domain knowledge but require some degree of technology support [24]. Patients have more urgent and stronger motivation for the use of technologies to cure or alleviate health conditions that they actually suffer from than normal users. Thus far, prior work has not covered technology readiness issues for average users whose average daily living habits may lead to health concerns. Our current study contributes to the literature by investigating and explaining how lay users – non-patients and non-professionals – are ready to accept technologies for preventative care in order to identify design guidelines to build personalized lifestyle management systems (PLMSs).

3 Conceptual model and research hypotheses

Our goal is to understand the average users' readiness for sensing technologies that could help them change their behaviors and cultivate healthy habits. We conceptualized a

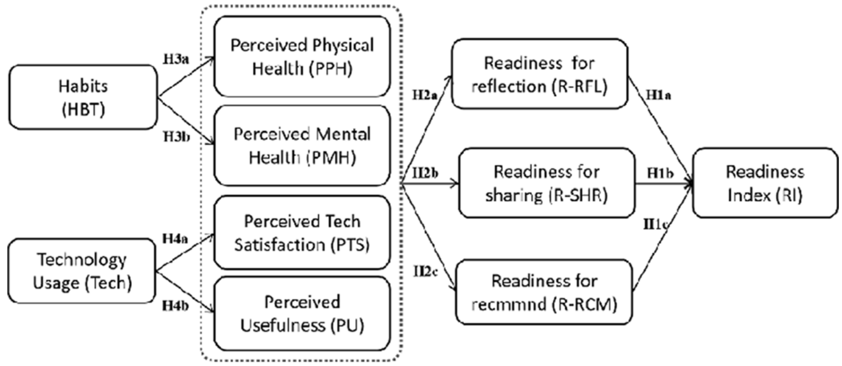


Fig. 1 General framework with hypothesized influence paths

model called EHR (e-health readiness) based on SAM [26] and Hoeger et al.'s book on well-being [7]. Besides readiness, this model also covers user perceptions on health and technology and how they are influenced by users' habits. We depict our research model and hypotheses in Fig. 1 and explain the constructs and hypotheses below.

3.1 Readiness

Readiness assesses overall user willingness to use lifestyle management systems and their willingness to use major methods in current technologies to motivate behavior change. Our model covers the following three methods: 1) help users monitor and reflect on their health data, 2) allow them to share the data in the social networks, mainly family members and friends, and 3) provide personalized health recommendations.

3.1.1 Overall readiness index

Overall readiness index, or readiness index (RI) for short, evaluates to what extent users are willing to use technologies to promote their personal well-being and to enhance lifestyle choices. This is a general readiness assessment without exposure to any concrete devices or systems.

3.1.2 Readiness for reflecting

Readiness for reflecting (R-RFL) on health condition evaluates users' willingness to monitor their health. Monitoring and reflecting on health related data becomes a core component with the development of mobile sensing. Notably, mobile sensing in daily life is now feasible with the appearance of smartphones that contain abundant sensors [3]. A recent survey by Yumak and Pu [4] has identified off-the-shelf wearable sensors for physical movement (accelerometers, gyroscope and altimeter), skin conductance (electro dermal activity, galvanic skin response), heart rate (electroencephalography, optical blood flow), oxygen saturation (pulse oximetry) and sleep quality (electroencephalography, actigraphy). Starting from single-sensor based devices for heart rate (e.g., Adidas MiCoach) or physical movement steps (e.g., Nike+iPod), we now see multi-sensor devices such as the BodyMedia armband, which combines four sensors (accelerometer, galvanic skin response, heart flux, temperature) to achieve higher accuracy in estimating the number of calories burnt by the body. Besides accuracy, another important issue is the obtrusiveness of these sensors to avoid disturbing users. Nowadays, many products embed sensors in shoes, bracelets, wristwatches or earphones [4]. Mobile sensing has provided a basis for users to monitor their activities, which further helps users reflect on their habits, make the correct decisions and change their behavior [2, 28].

3.1.3 Readiness for sharing

Readiness for sharing (R-SHR) health data assesses users' willingness to use technology to share data with families and friends. Many mobile apps also support users to share their fitness statistics using social media. Typical examples include Nike+, RunKeeper, My tnessPal. Previous studies have shown the effectiveness of motivating behavior change through sharing data with families or friends [28]. Connecting with families and friends can motivate users to fulfill their fitness goals [31]. Some of the earliest examples include the work from Consolvo et al. [29], Toscos et al. [17] and Chen and Pu [30] that investigate social fitness systems and strategies. Chen et al. showed that cooperation with others motivates users to do more exercise compared with competition [30]. Other studies also showed the promising effect of leveraging accountability in reaching fitness goals [32, 33]. Similar strategies have been applied to help users manage bodyweight [34], form a healthy habit of water-intake [35] and maintain healthy sleep habits [36]. Meanwhile, studies also indicted users' hesitation in sharing fitness data in the their social networks due to privacy concern and over-sharing.

3.1.4 Readiness for receiving recommendations

Readiness to receive recommendations (R-REC) evaluates users' inclinations to receive healthcare recommendations from the systems. Providing recommendation means proactively suggesting health practice to users based on their health goals and current behavior [21]. ShutEye [36] is a typical mobile recommender system to enhance user's sleep quality. It uses the wallpaper on mobile phones as a peripheral display for realtime sleep hygiene recommendations about common activities that are known to impact sleep relative to bed and wake times [36]. For example, ShutEye provides suggestions to users on the feasibility to drink coffee depending on the time of the day and expected sleeping time. Instead of relying on a sensor, the recommendation is based on preset goals of sleeping and waking time. As another example of health recommender, Calorie-aware Kitchen [39] helps users eat healthier by tracking the ingredients of cooking materials and providing calorie recommendations. A health recommender can serve as users' personal health assistant and consultant and thus help them make decisions about daily practices related with health.

In summary, technologies for behavior changes mainly use means that help users reflect on their health related habits, share the data in the social networks and receive personalized health recommendations. We thus propose the following hypothesis.

H1a: Readiness to monitor health using technologies positively impacts overall readiness index.

H1b: Readiness to share health data using technologies positively impacts overall readiness index.

H1c: Readiness to receive healthcare recommendations using technologies positively impacts overall readiness index.

3.2 Perceptions

Perceptions refer to a higher-level of user attitudes of their personal health (both physical and mental). Different from objective health index, which is normally measured with medical equipment [26], perceived healthiness is users' subjective feeling of their health conditions. We consider perceived healthiness more appropriate for average users than objective health index, which is frequently used by patients or professionals. Perceptions also include users' attitudes towards well-being-assisting technologies. We further categorize perceptions into the following aspects:

- Perceived physical healthiness (PPH) refers to users' self-perceptions about the physical well-being of their current lifestyle. This element requires users' opinions on how much they find themselves living a healthy lifestyle as well as whether or not they are satisfied with their body weight.
- Perceived mental health (PMH) measures users' satisfaction to their mental well-being. This element focuses on whether users deal with temporary negative feelings effectively, such as disappointment, sadness, loneliness, and depression.
- Technology satisfaction (PTS) determines the degree to which users are happy about technologies. It is an *overall* assessment of how much users believe technologies have improved their lives as well as how much users can tolerate encountered challenges and frustrations when dealing with technologies.
- Perceived usefulness (PU) refers to the degree to which users expect that the usefulness can compensate their privacy concerns when using such technologies.

Clinical studies show that patients' physical health and mental health, as well as expected usefulness of health sensors can influence their attitudes towards various aspects of sensor technology and thus having an impact on their overall adoption intention [26]. Therefore, we proposed the following hypotheses.

H2a: Perceptions on health, technology satisfaction and expected usefulness have a positive effect on readiness to adopt technology to monitor health.

H2b: Perceptions on health, technology satisfaction and expected usefulness have a positive effect on readiness to adopt technology to share health related data in the social networks.

H2c: Perceptions on health, technology satisfaction and expected usefulness have a positive effect on readiness to adopt technology to receive health recommendations.

3.3 Habits

Habits refer to users' current practice and behavior concerning well-being and technology usage. They are the exogenous variables of the model. We focus on the following essential dimensions: food intake, physical activities, sleep, stress management, social activities and technology usage, based on the domain knowledge acquired from Hoeger et al.'s book on well-being [7].

- Food intake (FI) refers to users' current eating habits. A healthy habit of food intake involves regularity of meal take, variety of food choice, limited saturate fat, avoidance of unnecessary snacks and so on.

- Physical activities (PA) refer to users' practices of physical activities, mainly including the frequency and regularity of physical exercise.
- Social activities (SA) focus on users' personal relationship with friends and family and their participations in social events with them.
- Sleep (SL) refers to users' sleep hygiene, including regularity and sufficiency of sleep.
- Stress management (SM) mainly concerns with two aspects: whether users can readily recognize stress and whether they are able to perform effective stress management techniques.

Behavioral scientists found that users' health habits and lifestyles are strongly correlated with their perception of physical and mental health [6]. Thus, we hypothesized the following.

H3a: Health habits influence the perceptions of physical healthiness.
H3b: Health habits influence the perceptions of mental healthiness.

- Technology Usage (Tech) concentrates on users' present behavior when using technologies, such as the frequency of using technologies.

We posited the following hypothesis.

H4a: There is a positive relationship between current technology usage and perceived technology satisfaction.
H4b: There is a positive relationship between current technology usage and perceived technology usefulness.

4 Model evaluation

4.1 Experiment setup

To validate our conceptualized model, we developed a structured online survey. The survey questions focus on users' current habits about their well-being, their self-perceptions of overall health, their current levels of technology usage and their willingness to adopt technology for well-being. The initial set of questions were designed based on the domain knowledge acquired from Hoeger et al. [7]'s book on well-being and based on literature survey mentioned in the previous sections.

We first conducted an iterative semi-structured interview with three users to check the competency and quality of the initial set of questions, including the completeness, appropriateness and wording. The interview helped us ensure that the terms we derived from the book and wording of the questions are easily understandable for participants. Following that we launched a small-scale pilot study (N = 12) to test the procedure of data collection. The purpose of the pilot study is to verify the procedure of the online survey and further test the understandability of the survey questions. We then finalized the questionnaire based on the findings from the interview and feedback on the pilot study.

The online survey consists of three major sections: introduction, a demographic survey, and main questions. The introduction part concerns the purpose, procedure and privacy policy of the survey. Demographic questions include age, gender, nationality, occupation, marital status and IT proficiency levels. The main section of the questionnaire consists of 51 questions that cover items in our model in the form of Likert scale questions with options from strongly disagree (1) to strongly agree (5) and an open-ended question at the end. Note that we deliberately produce redundant questions in the form of reverse scored items or synonyms to check irresponsible answers and control data quality. Each Likert scale question is followed by a text box allowing participants to input their detailed comments to support their answers.

The large-scale online survey was conducted on Amazon Mechanical Turk (AMT). We set 50 cents per person as the user incentive to complete the survey. One recent research work by Gabriele et al. [40] suggests that AMT can be considered as a viable method for data collection if the data quality is controlled. We therefore conducted several checks to ensure that random and irresponsible answers are discarded. The online survey was launched on AMT at 2pm on May 28th (CEST) and closed at 9pm on May 28th in 2012. Within these 7 h, 621 participants successfully completed the survey and submitted their answers, which shows that AMT is an effective platform to recruit users for large-scale surveys.

4.2 Data description and participants

To ensure the quality of users' answers, we filtered outlier entries such as robots and irresponsible Turkers. Firstly, we detected potential automatic bots by examining the elapsed time for each participant to complete the survey. If the elapsed time was less than 3 min, that participant was considered as a robot or invalid participant as it was unlikely for a human with average reading and clicking speed to answer every question in 3.5 s. Secondly, we computed the variance of each participant's answers for all questions. We discarded respondents with zero variance, showing that they did not have the natural variation in their answers. The third test was inconsistency check of users' answers by examining the pairs of redundant questions with the same meaning or reverse scale. If their answers were very different, i.e. the absolute value of the difference was four, a contradiction in their answers was found. Based on the above three criteria,

Table 1 Profile of participants (N = 541)

	Item	N	Pct.
Age	Below 20	43	7.95%
	31–40	330	61.00%
	31–40	111	20.52%
	41–50	38	7.02%
	Above 50	19	3.51%
Gender	Male	356	65.80%
	Female	185	34.20%
Nationality	India	327	60.44%
	USA	101	18.67%
	Others	113	20.89%
Occupation	Student	152	28.10%
	Office worker	96	17.74%
	House worker	45	8.32%
	IT-related jobs	30	5.55%
	Teacher	26	4.81%
	Others	192	35.49%
IT proficiency	Beginner	68	12.57%
	Average	301	55.64%
	Advanced	172	31.79%

we created a list of potential robots as well as invalid respondents who we believed did not provide reliable answers and we eliminated a total of 80 of them (representing 12% of the total sample size) from further data analysis. Thus, the final sampling size of valid users became 541.

Among these 541 participants, more than 60% were in the 21–30 age group, and around 20% were in the 31–40 age group, with the rest of them distributed in the other three age groups. Over 65% of them were male and the nearly 35% were female. As for nationality, the majority of participants were from India (60.4%) and the USA (18.7%), while the rest of them distributed diversely in other countries worldwide (e.g. UK, France, Romania, Philippines). Their occupations were also diverse: 28.0% were students, 17.7% were office workers and the remaining included house workers, IT-related jobs and teachers and etc. More than half (55.6%) of the participants indicated having an average proficiency in using IT, and those who had low and high proficiency were 12.6% and 31.8% respectively. Details are shown in Table 1.

4.3 Analysis methods

We first checked the rationality of each construct in our proposed model and their relations by applying confirmatory factor analysis (CFA) [21] using SPSS. It helps us validate the hypothesis that a relationship between multiple observed variables and the underlying latent constructs exist. The results of CFA is presented in Section 4.5. We then conduct the path analysis in structural equation modeling (SEM) using AMOS to examine the causal relationship between the latent variables in the model [21]. We report the findings of SEM in Section 4.6.

4.4 Data screening

Before validating the model, we conducted data screening to ensure the dataset is useful, reliable and valid for testing causal relationship [41]. The data pass the test of missing data, which means the 541 data entries are complete. The second test, normality test, is an assumption of SEM test and checks whether the data for all variables is well modeled by a normal distribution. Results show that the skewness of all variables falls within a range of $[-2, 2]$, the recommended acceptable range of normality test for Likert scale questions [42]. Thus our data also meet normality requirement. We also tested the linearity between each pair of variables (1275 test in total) using SPSS to confirm the data are ready for confirmatory factor analysis.

4.5 Model validity and reliability

To verify the model, we first computed the internal consistency and reliability of the model using Cronbach's alpha and item-to-total correlations. This process aimed at revealing internal consistencies of a given construct and identifying the clusters of related variables as well. The items with low correlated item-total correlations (<0.40) were discarded or regrouped into another construct. After several iterations, we obtained values as presented in Table 2. We refer to the cut-off points (Cronbach's alpha <0.50, item-total correlation <0.40) according to Peterson's recommendation [24].

We then examined the convergent validity of the measured items by factor loading and composite reliability. Factor loadings of all items in each construct exceeded the acceptable level of 0.50 [21]. Most of the composite reliabilities also exceeded the recommended level of .80. Therefore, the results demonstrated a convergent validity of the measurement items (see Table 2).

We also evaluated the discriminant validity via inter-construct correlations (see Table 3). Correlations between any two constructs were all less than the square root value of average variances that are shown in the diagonal, which represents a level of appropriate discriminant validity. The only exceptions are between physical activities (PA) and perceived physical health (PPH), and between social activities (SA) and perceived mental health (PMH). Since the two constructs are interconnected [43], we consider them as acceptable for our model.

Table 2 Test results of internal reliability and convergent validity

Constructs	N	Internal reliability		Convergent validity		
		Cronb alpha (0.5)	Item-total correlation (0.4)	Factor loading (0.5)	Composite reliability (0.8)	Variance extracted (0.5)
1. Food Intake (FI)	3	.729			.841	.840
I limit the amount of saturated fat and trans fats in my diet on most days of the weeks			.544	.801		
I regularly avoid snacks, especially those that are high in calories and fat			.572	.820		
I pay attention to the total amount of calories that I intake each day			.539	.796		
2. Physical Activities (PA)	2	.567			.869	.869
I participate in physical activities at least 20 minutes per day, 3 days per week			.400	.769		
I like to seek additional opportunities to be active each day (e.g. walking, cycling, parking farther away, gardening)			.400	.773		
3. Social Activities (SA)	5	.755			.800	.798
I routinely participate in social activities with family or friends			.516	.781		
I have close personal relationships with other people who I trust and rely on			.540	.742		
I have a network of friends who enjoy the same social activities I do			.546	.818		
I associate with people who have a positive attitude about life			.462	.728		
I have close friends and family members with whom I can discuss personal problems and approach for help when needed and with whom I can express my feelings freely			.544	.732		
4. Sleep (SL)	2	.737			.948	.948
I regularly sleep 7 to 8 h per night			.583	.890		
I get enough rest/sleep every day			.583	.890		
5. Stress management (SM)	2	.646			.915	.915
I readily recognize stress and act on it when I am under excessive tension			.477	.859		
I am able to perform effective stress management techniques			.477	.859		

Table 2 (continued)

Constructs	N	Internal reliability		Convergent validity		
		Cronb alpha (0.5)	Item-total correlation (0.4)	Factor loading (0.5)	Composite reliability (0.8)	Variance extracted (0.5)
6. Technology usage (Tech)	1					
IT technology is currently a big part of my daily life						
7. Perceived Physical health (PPH)	2	.563			.889	.889
I consider myself having a healthy lifestyle			.407	.839		
I maintain recommended body weight (includes avoidance of excessive body fat, excessive thinness, or frequent fluctuations in body weight)			.407	.839		
8. Perceived Mental Health (PMH)	2	.613			.905	.905
I can deal effectively with disappointments and temporary feelings of sadness, loneliness and depression			.448	.851		
I respond to temporary setbacks by making the best of the circumstances and by moving ahead with optimism and energy			.448	.851		
9. Perceived Technology Satisfaction (PTS)	2	.490			.853	.853
The amount of frustrations or challenges I encountered when using IT technology is tolerable			.324	.814		
I think IT technology helps improve my daily life			.324	.814		
10. Perceived Usefulness (PU)	1					
I think there would be significant benefits that can compensate my privacy concerns if I use such technologies						
11. Readiness for reflection (R-RFL)	1					
I would be interested in using IT technology to monitor my physical and emotional conditions, given privacy is not a concern						
12. Readiness for sharing (R-SHR)	1					
I am willing to share my health and diet data with my family and friends, providing this data is used to improve our overall wellness						

Table 2 (continued)

Constructs	N	Internal reliability		Convergent validity		
		Cronb alpha (0.5)	Item-total correlation (0.4)	Factor loading (0.5)	Composite reliability (0.8)	Variance extracted (0.5)
13. Readiness for recommendation (R-RCM)	1					
I am willing to receive recommendations from an IT system to improve my personal well-being, given privacy is not a concern						
14. Readiness Index (RI)	1					
In general, I am willing to use IT technologies to improve my lifestyle choices						

Constructs with single item are included for completeness

In summary, our model was validated as robust and satisfactory in terms of its internal consistency reliability and the convergent and discriminant validity.

4.6 Structural equation modeling

We tested the overall model fit, which evaluated our hypotheses on the causal relationships among the four layers. Figure 2 presents the results of the structural model analysis with the corresponding values of R2 (coefficients of determination) and path loadings. All the R2 estimates are larger than the threshold of .10 and p-values are less than .10, indicating they are appropriate to examine the significance of the paths. The model goodness-of-fit indexes are: Chi-square = 761.227 (d.f. = 278), Chi-square/df = 2.738 (<3 [44]), p = .000, GFI = .903 (>.90 [45]), CFI = .864 (>.85 [45]), RMSEA = .057 (<.06 [44]), which all met the recommended thresholds to be an appropriate model.

The results show that users' readiness index is significantly influenced by their willingness to use personalized lifestyle management systems (PLMS) to monitor their health conditions ($\beta = .13$, $p < .01$), to share data with friends and families ($\beta = .39$, $p < .01$) and to receive recommendation from the systems ($\beta = .22$, $p < .01$). Among these factors, willingness to share data has the most salient determining effect on overall readiness index. The above results validate H1 that users' attitudes on using technology to reflect, share and receive recommendations on their health have determining effects on their overall readiness for such tools. Furthermore, the above finding indicates users' readiness to share their health data and to receive healthcare recommendations has a large impact on their overall readiness to adopt such technology. This finding uncovers the necessity to balance on the functions of designing such technology. To the best of our knowledge, current PLMSs have focused on helping users to reflect on their health [30]. Admittedly, monitoring and reflecting on health data are a basis of sharing and recommendation, especially when this field is still developing. Meanwhile, our results suggest that it is promising to balance and shift towards functions such as social sharing and health recommendation may increase user acceptance of PLMSs.

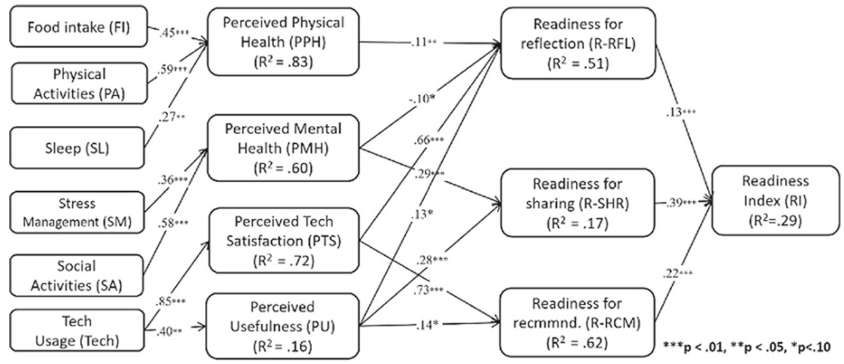
Table 3 Inter-construct correlation matrix

	1	2	3	4	5	6	7	8
1. FI	.793							
2. PA	.499	.615						
3. SA	.355	.505	.654					
4. SL	.257	.319	.435	.870				
5. SM	.535	.422	.422	.373	.839			
6. PPH	.719	.829	.550	.456	.797	.609		
7. PMH	.324	.312	.680	.434	.574	.402	.631	
8. PTS	.177	.177	.386	.215	.201	.214	.295	.459

Design implication 1 Besides self-monitoring, consider incorporating social sharing and recommendation in sensor technology to enhance the chance of user acceptance.

As for users' willingness to reflect on their health condition using technologies, we found that it was positively influenced by their perceived physical health ($\beta = .11$, $p < .05$), technology satisfaction ($\beta = .66$, $p < .01$) and expected usefulness ($\beta = .13$, $p < .10$), but negatively influenced by users' mental health ($\beta = -.10$, $p < .10$). The results confirm H2a that users' perceptions

Fig. 2 Structural model fit



of physical health, mental health and technology satisfaction and expected usefulness lead to their attitudes towards monitoring health conditions using PLMS. Noticeably, technology satisfaction is the dominant determining factor in user readiness for PLMS. It is likely that technology savvies are more likely to accept using technology to monitor their health. Interestingly, the more a user perceives him as physically healthy, the more likely he is willing to use PLMS to reflect on his health data, but the less he perceives himself as mentally healthy, the more he is likely to monitor his health data. We thus propose the following implication for designing technology for self-reflection.

Design implication 2 Consider adapting the technology for less advanced IT users or involving them in using the technology to monitor and reflect on their health.

Users' willingness to share data with significant others is positively predicted by their mental health ($\beta = .29$, $p < .01$) and expected usefulness ($\beta = .28$, $p < .01$), showing that users who perceive themselves as mentally healthy are more willing to share their data with their friends and families. However, no significant determining effect was found between willingness to share and their perceived physical health. This partially verifies H2b that users' perceived mental health and expected usefulness of technological tools have leading effects on their attitudes for sharing data using PLMS. It is worth mentioning that perceived mental health has a positive influence on intention to share compared with a negative impact on intention to self-monitor. It is possible that users are less likely to share their data if they are in less desirable mental conditions in order not to cause their families or friends worried. We thus summarize the implications for designing technologies that help users to reflect on health.

Design implication 3.1 Consider designing features that enhance users' perceived mental health to encourage their willingness to share health related data.

Design implication 3.2 Willingness to share is independent of users' technology satisfaction.

In addition, users' willingness to receive recommendations is predicted by their technology satisfaction ($\beta = .73$, $p < .01$) and expected usefulness ($\beta = .14$, $p < .10$). Notably, the influence from technology satisfaction is dominant. One explanation is that users who have higher technology satisfactions feel more comfortable with medical suggestions from machines than less satisfied users. However, no significant regression weight is found between their willingness to receive recommendations and their perceived physical or mental health. This suggests that users' intention to receive recommendations is independent of their healthiness. Thus, the findings partially verify H2c that users' perception of technology satisfaction and expected usefulness significantly affect their attitudes for receiving health related recommendations from PLMS. We thus propose the following to design technology that provide health recommendations to users.

Design implication 4.1 Readiness to receive recommendation is dominantly decided by technology satisfaction; thus, consider the technical proficiency of the user population when designing lifestyle management systems.

Design implication 4.2 Readiness to receive recommendation is independent of health conditions.

Finally, people's perceived physical health on their lifestyle is significantly influenced by their habits in food intake ($\beta = .45$, $p < .01$), physical activities ($\beta = .59$, $p < .01$) and sleep practices ($\beta = .27$, $p < .05$). Among them, their physical activities practices have the dominant effect ($\beta > .59$). Additionally, users' social activities ($\beta = .58$, $p < 0.01$) and stress management ($\beta = .36$, $p < .01$) highly lead to their perceived mental health. Thus, this verifies H3 that users' habits influence their perceived healthiness. Furthermore, people's current technology usage strongly influences their perceived satisfaction when using technology ($\beta = .85$, $p < .01$) as well as their expected usefulness of technology ($\beta = .40$, $p < .05$). This confirms and elaborates H4 that users' technology usage significantly impacts their technology satisfaction and perceived usefulness of PLMS.

While health is a comprehensive index involving multiple facets, our results show habits in the different facets weigh differently in users' perceptions on their health. Therefore, we propose the following design implications.

Design implication 5.1 Physical activities have the most salient determining effects for user perceived physical health; thus when designing technologies for support users' physical health, consider promoting users' physical activities, while educating users on other aspects of health practices, such as food intake and sleep to help users gain a balanced perception of physical health.

Design implication 5.2 Social activities play a vital role in user perceived mental health; thus when designing technologies for mental health, consider supporting social activities, while encouraging users to manage their stress.

5 Motivations and concerns

We further analyzed users' comments for the survey questions related with user readiness to understand their motivations and concerns for adopting technologies to change their health-related behavior. The examined statements include willingness to monitor lifestyle, to share data and to receive recommendation and overall readiness index. For each statement, three researchers iteratively encoded each comment entry with -1 (negative attitude), 0 (neutral attitude) or 1 (positive attitude). We then extract users' motivations from positive and neutral statements and concerns from negative and neutral statements. In the following subsections, we report findings of users' comments for the four statements.

5.1 Readiness to monitor lifestyle

Users' readiness to monitor lifestyle is assessed using the following statement: "I would be interested in using IT technology to monitor my physical and emotional conditions, given privacy is not a concern." The following themes emerged from the comments ($N = 163$) we have collected.

The motivations of monitoring health conditions differ from novice users to experienced users, i.e., those who have used similar technologies before. Novice users are mainly driven by curiosity and novelty of such technology. Experienced users, on the other hand, care more about the effectiveness of such tools. For example, P144 believes "technology could help me see patterns and avoid certain situations (diseases)", and P76, who have used a game called Journey to the Wild Divine that integrates monitor heart rate and skin conductance, considers it very helpful and he "would love a more portable and accurate tool like that."

The concerns of adoption can be summarized into three aspects: reliability, privacy and technology overload. Doubt in reliability mainly refers to users' skepticism about whether technology can be sufficiently intelligent to understand users' health condition, e.g., P183 "don't know how realistic such technology would be" and P428 didn't believe "IT can understand human emotions." Privacy concern, as a second pediment, is more visible in monitoring emotional conditions than physical conditions. Four users (P102, P404, P418 and P501) have mentioned they were willing to monitor physical condition but not emotional condition due to privacy concern. Technology overload is concerned with users' notion that being less attached to technology is essential to a healthy life. For instance, P311 commented, "I have had enough of IT in my everyday life. Don't want to use it to monitor my health anymore."

5.2 Readiness to share data

We identified users' attitudes towards sharing data by their comments for the statement "I am willing to share my health and diet data with my family and friends, providing this data is used to improve our overall wellness." We summarize our findings from 164 comment entries.

The major motivation for sharing is to enhance the awareness of other people's lifestyle. More specifically, some users are interested in helping their families or friends to become healthier by sharing their own tips in keeping fit. For instance, even though P173 "don't follow good dietary habits", he does "have good knowledge on how to stay healthy will be interested to share tips." Some are interested in knowing other people's lifestyle to compare and learn from them. "It will help me to get an idea about activities of various kinds of people and adopt some good practices", commented by P512. However, users have emphasized the importance of whom to share. Most of them are mainly interested in sharing with close-knit groups, e.g., family members and friends. Some also expressed their concerns about making their families worry if they are in ad emotional states.

5.3 Readiness to receive recommendations

Users' readiness to receive recommendation is evaluated by the statement "I am willing to receive recommendations from an IT system to improve my personal well-being, given privacy is not a concern." The comments ($N = 154$) mainly shed light on the merits and constraints of providing recommendations from IT systems. Convenience is the major benefit. If such technology is intelligent enough, users can “avoid traveling for a doctor” (P109), “cut down medical expenses” (P204) and “keep updated about health advice” (P338). For some users, receiving frequent health related information is already a daily practice. As P453 commented, “Yes, I have already subscribed to many health journals.” Receiving recommendations from machines also have the advantage to circumvent embarrassment when patients have to explain some symptoms to their doctors. As P506 reported, “I would allow technology to make these decisions for me. I was so embarrassed to admit to my doctor that I was depressed and I dread having to speak with her about it. I’m ashamed that I couldn’t handle it on my own.” Users’ comments have showed their inclination to bring healthy behavior to everyday life before it becomes necessary to go to the hospital or visit a doctor. The major concerns about receiving recommendations can be summarized into skepticism about the authority and tone of recommendations. Authority refers to a user’s doubts about the source of recommendations, e.g., whether the recommendations are from doctors, experts or scientific research. Users tend to assign less trust when the recommendations are from a machine. It is also worth mentioning that users may pay less attention to advice from machines than from humans, i.e., experts. “I doubt I will listen to a machine. The tone of these recommendations must be very carefully managed”, said P539. “I would rather get the info from a doctor so I can directly ask questions.” Thus, the way of delivering recommendations should be carefully considered by designers.

5.4 Overall readiness of adoption

We then summarize the technological requirements for tools that help users to change their behaviors, as derived from the comments (N = 171) of the following statement “In general I am willing to use IT technologies to improve my lifestyle choices.” Firstly and dominantly, users require such devices to be reliable: “I hope technologies can provide more accurate and reliable measurements than a human.” Second, users are more willing to adopt trendy technology, because they “like the latest trend” (P266). Third, such tools should be simple and not distractive, since users “don’t want to add burden and make life inconvenient” (P338). Finally, cost matters. As users P578 concerned, “I would consider buying one if it helps a lot; but if it costs a lot, I may hesitate.” These findings also accord with Yumak’s survey about requirements for sensor based health management systems [4].

6 Conclusions

Using sensing technologies to support personalized lifestyle changes has gained increasing attention recently. However, users’ readiness and acceptance intention still remains an open subject of study. To investigate this issue, we conceptualized EHR, an acceptance model that examines the relationship between users’ health habits and their readiness to accept sensing technologies for personalized lifestyle change. Specifically, this model targets at lay users, i.e., non-patients and non-professionals.

The results from an online survey (N = 541) confirm that our model provides validity and reliability of its structure, and that the proven paths carry meaningful causal relationship among the constructs. The model also offers a number of implications in design technologies that support behavior change. First, users’ willingness to share data has highest determining effect ($\beta = .39$) on overall e-health acceptance, followed by readiness to receive recommendations ($\beta = .22$) and inclinations to reflect on health conditions ($\beta = .13$). While this field is rapidly developing in helping users monitor their health data, which is a prerequisite for pervasive healthcare, our results also indicate user needs towards social sharing and receiving health recommendations. Secondly, user acceptance for the above three functions is associated with perceived physical health, perceived mental health, technology usage and perceived usefulness of such technology in different ways. Concretely, user readiness for using technology to monitor their health and receive recommendations are dominantly decided by their technology satisfaction, while readiness to share is independent of technology usage; willingness to monitor health is significantly affected by user perceived physical and mental health, willingness to share is only influenced by their perceived mental health, and willingness to receive recommendation is independent of their perceived health conditions. Third, the model shows users’ health habits in various aspects influence their perceived physical and mental health with different weights. Since our work studies user needs and perceptions before their exposure to any concrete systems, it provides insight for practitioners to design user-friendly tools.

This research has limitations. We are aware that the majority of the sampled subjects are young people and a great proportion of them are from India. They are likely to be curious about novel technologies. It’s worth extending the study with elder age group and users from various cultures to validate the generalizability. In the future, we will continue the study with a wider diversity of users and extend EHR to post-usage phase and investigate adoption and retention of such systems and derive system design guidelines for behavior change.

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