Health Behavior Change in HCI: Trends, Patterns, and Opportunities

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Figure 1: The paper frequency distribution in the field of health behavior change in the HCI community. Note that we extracted the original data from the ACM digital library on August 23, 2018, when some conferences for this year have not taken place. The majority of the papers are from conference proceedings, while a small part of them are from journals (e.g., Personal and Ubiquitous Computing or PUC in the figure).

ABSTRACT

Unhealthy lifestyles could cause many chronic diseases, which bring patients and their families much burden. Research has shown the potential of digital technologies for supporting health behavior change to help us prevent these chronic diseases. The HCI community has contributed to the research on health behavior change for more than a decade. In this paper, we aim to explore the research trends and patterns of health behavior change in HCI. Our systematic review showed that physical activity drew much more attention than other behaviors. Most of the participants in the reviewed studies were adults, while children and the elderly were much less addressed. Also, we found there is a lack of standardized approaches to evaluating the user experience of interventions for health behavior change in HCI.

Based on the reviewed studies, we provide suggestions and research opportunities on six topics, e.g., game integration, social support, and relevant AI application.

CCS CONCEPTS

• H5.2. User Interfaces: User Design; Theory & Methods • J.3. Computer applications: Life and medical sciences (Health)

KEYWORDS

Systematic review, Health behavior change, Behavioral theories, Behavior change strategies, Intervention characteristics.

ACM Reference format:

FirstName Surname, FirstName Surname and FirstName Surname. 2018. Insert Your Title Here. In Proceedings of ACM Woodstock conference (WOODSTOCK’18). ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/1234567890

1 Introduction

Our daily behaviors heavily influence our health. According to the County Health Rankings [43], variation in health can be
accounted for by health behaviors (30%), clinical care (20%), social and economic factors (40%), and physical environment (10%). Increasing evidence has shown that unhealthy behaviors - such as the unbalanced diet, inadequate physical activity, sleeping deprivation, drinking alcohol, and smoking - play an important role in individuals’ health. Chronic diseases caused by unhealthy behaviors and habits are among the leading causes of mortality [18]. Some of the chronic diseases, e.g., type 2 diabetes, could be life-long and bring a heavy burden to the patients and their families. The only way to prevent many chronic diseases is to change unhealthy behaviors in the long term.

The research on digital technologies to support health behavior change is no doubt a vital task for the Human-Computer Interaction (HCI) community. Only in the proceedings of the ACM CHI conference until 2018, we found 310 papers mentioning “behavior change.” However, it seems that the interest in health behavior change from the HCI community began to decrease recently. We see this trend by searching and screening the related papers from the ACM digital library. The amounts of the related papers from both the CHI conference and the UbiComp conference have seen the decrease since 2016, and the corresponding paper amount in CHI 2018 has fallen back to the level in 2014 (see Figure 1). To get an insight into this phenomenon, we conducted a systematic review of the papers about health behavior change from the HCI community. We extracted information from the perspectives of the target behavior, the target user group, the used behavioral theories, the deployed behavior change strategies, the intervention characteristics, and evaluation methods.

The remainder of this paper is organized as follows: The next section introduces behavioral theories, behavior change strategies, and behavioral intervention characteristics as the apparatus of our review. In Sect. 3, we show our methods to search, select, and code the studies. Sect. 4 reports our findings on research trends and patterns of health behavior change in HCI. Based on our reviewed studies, in Sect. 5, we provide suggestions and opportunities for the future research in six topics. Finally, we show the limitations of our work and conclude the paper.

2 Background

2.1 Behavioral Theories

Behavioral theories refer to the social-psychological theories of behavior change, which explain and predict human behavior. Glanz et al. [34] listed the most frequently used behavioral theories published before 2010: the Social Cognitive Theory (SCT) [3], the Transtheoretical Model of Change (TTM) [76], the Health Belief Model (HBM) [79], and the Theory of Planned Behavior (TPB) [2]. As explained by Sutton [80], each of the behavioral theories specifies a small number of cognitive and affective factors as the proximal determinants of behavior.

In a CHI paper in 2013, Hekler and colleagues illustrated the (dis)advantages of behavioral theories and how HCI researchers can use and contribute to behavioral theories [38]. In summary, behavioral theories can help inform design, guide evaluation strategies, and select target users. Also, HCI researchers have the change to improve behavioral theories by improving measurement, enhancing early-stage theory fidelity testing, and supporting and using big data and A/B testing. Following this implication, we will reveal how HCI research engaged with behavioral theories in the real world.

2.2 Behavior Change Techniques (Strategies)

Behavior change techniques (BCTs) are defined as observable, replicable, and irreducible components of an intervention designed to change behavior [1,59], e.g., self-monitoring of behavior and goal setting. Abraham and Michie published the taxonomy containing 93 BCTs in 16 groups in 2013, called Behavior Change Technique Taxonomy (v1) [59]. The BCT taxonomy has been used for informing intervention development [64,65] and identifying the effective ingredients in intervention studies for health behavior change [24,33,58,71] and products (i.e., health-oriented apps [17,20,23,60] and wearables [54]).

In Figure 2, we show the relative use frequencies of BCTs used in 405 studies. In the HCI community, however, BCT taxonomy is not used as widely as the model of Persuasive Technology [29] or Persuasive System Design (PSD) [70]. The model of PSD includes 28 principles in four categories, namely primary task support, dialogue support, system credibility support, and social support.

Figure 2: The word cloud of behavior change strategies coded from the papers listed on the official website1 of BCT taxonomy (N=405). The bigger the font is, the more frequently the strategy was used.

In comparison with PSD principles, BCT taxonomy provides a more comprehensive pool of strategies for behavior change interventions. Even though, BCT taxonomy does not cover all the strategies we have found in related studies. Therefore, we add another five strategies to BCT taxonomy for our coding, which include social cooperation, social competition, social recognition, virtual reward, and game integration. The former three are derived from PSD principles. By game integration, we mean both exergames [63] and gamification [61].

1 http://www.bcttaxonomy.com/interventions
2.3 The Behavioral Intervention Characteristics

The behavior change strategies are only about “what” but not “how” of the intervention. In 2014, Mohr and colleagues proposed the behavioral intervention technology (BIT) model to support the translation from behavior change intervention aims into an implementable treatment model [62]. Inspired by the BIT model, we include the concepts of intervention characteristics and intervention workflow in our coding, which can help us analyze how interventions are delivered. The characteristics include the medium, the visualization method (related to aesthetics), and the social support type in our coding. We further elaborate the details in the following section.

2.4 The Holistic Framework

In prior work, we proposed a holistic framework to guide the design and report of health behavior change interventions [88]. This framework integrates the three mentioned aspects in this section. By following this framework, we aim to provide the most comprehensive review of health behavior change in HCI. We emphasize comprehensiveness and consistency in reviewing health behavior change because health behavior change studies are always complex processes and affected by many aspects in field studies.

2.5 Related Work

In a highly related work in 2016, Orji and Moffatt [73] reviewed how persuasive technology was used for health and wellness in 85 related papers. They coded the reviewed studies from 11 perspectives: targeted (health) domain, technology, duration of evaluation, behavior theories, motivational strategies, evaluation method, targeted age group, number of participants, study country, targeted behavioral or psychological outcome, and findings/results. However, the coding of motivational strategies did not follow any existing taxonomy of persuasive technology (e.g., PSD principles) or behavior change techniques (e.g., BCT taxonomy). Thus the definitions of these strategies can be vague and imprecise for readers. We use a taxonomy integrating BCTs and PSD principles to code and analyze the adopted digital health strategies. Using the holistic framework [88] can help to achieve a more comprehensive review of the related studies.

Since existing systematic review on the effectiveness of digital health interventions have pointed out that there are not enough high-quality studies to draw powerful conclusion on effectiveness - e.g., eating behavior change [57] and sedentary behavior change at work [90] - we put our effort on revealing the patterns and trends of the existing empirical studies. We focus on multiple health behaviors instead of a specific one because we want to find out the patterns in different target behaviors.

3 Methods

As our initial aim is to find the research trends and patterns of health behavior change in the HCI community, we only used ACM digital library as our search repository, which covers most of HCI conference proceedings (e.g., CHI and UbiComp). For the searching, we considered the spelling versions of behavior/behaviour, similar expressions of behavior/behavioral change, persuasive technology, and the names of targeted behavior (e.g., physical activity and alcohol). We also excluded the papers focusing on sustainability, since they are out of the scope of this paper. The search was conducted on 23rd Aug. 2018, and the query syntax we used in ACM digital library is shown in Table 1.

Table 1: The query syntax used in ACM digital library.

| Query Syntax                                                                 |
|------------------------------------------------------------------------------|
| keywords.author.keyword:(+behavior +change -sustainability)                  |
| OR keywords.author.keyword:(+behavioral +change -sustainability) OR          |
| keywords.author.keyword:(+behaviour +change -sustainability) OR               |
| keywords.author.keyword:(+behavioural +change -sustainability) OR             |
| keywords.author.keyword:(+persuasive +technology -sustainability) OR          |
| keywords.author.keyword:(+physical +activity) OR                             |
| keywords.author.keyword:(diet +dietary) OR                                   |
| keywords.author.keyword:(+sexual +health) OR                                 |
| keywords.author.keyword:(smoking) OR                                         |
| keywords.author.keyword:(sleeping) OR                                        |
| keywords.author.keyword:(sedentary +sitting) OR                              |
| keywords.author.keyword:(alcohol) OR                                         |

Figure 3: The workflow of screening and selecting papers.

The four-phase flow diagram of PRISMA [49] was used to illustrate the study selection process (see Figure 3). A total of 1070 papers were identified out of 530,358 records in ACM digital library. The first author screened the records from the paper title. 354 records were screened out because of duplication (N=15), not being relevant to health behavior change (N=337), or being the workshop introduction (N=2). Afterward, the first
author reviewed the abstracts (or full paper if necessary) for the rest of the papers (N=776) and labeled the papers by the research method (see Table 2 for details) and target behavior. We further excluded the papers of duplication (N=10), not about health behavior change (N=72), workshop introductions (N=2), panel introductions (N=3), Ph.D. colloquia (N=20), courses & tutorials & talk introductions (N=4), and not in English (N=2). Finally, we obtained 648 papers falling into the listed types in Table 2. The paper list can be found in the supplementary material.

Table 2: The paper types used in our coding.

| Type                | Explanation                                                                 |
|---------------------|-----------------------------------------------------------------------------|
| Compared intervention study | It includes at least one user intervention session with at least two compared conditions. |
| Exploration study    | It includes at least one user intervention session for behavioral factors exploration without compared conditions |
| Test study           | It is a feasibility test or pilot study without enough measures of users’ behavior or outcome. |
| Design               | It is about designing systems or methods to support health behavior change without any user intervention. |
| Interview            | It includes only user interviews without any user intervention. |
| Survey               | It includes only surveys based on questionnaires without any intervention to users. |
| Data mining          | It is about systems/algorithms to detect, recognize, classify, or predict human behavior or behavioral factors for health behavior change. |
| Review               | It overviews or reviews previous work.                                      |
| Framework & Theory   | It proposes frameworks or theories for the research on health behavior change. |
| Viewpoint            | It provides viewpoints, guidelines, or implications for the research on health behavior change. |
| Concept              | It includes only concepts of systems or methods for health behavior change.  |

From the 648 papers in the phase of eligibility, we selected 72 papers that include compared intervention studies (73 studies in total). Afterward, two of the authors coded these full papers separately, and the differences were resolved by discussion. The coding schema is shown in Table 3.

Table 3: The coding items and explanations.

| No. | Item                          | Explanation                                                                 |
|-----|-------------------------------|-----------------------------------------------------------------------------|
| 1   | Target behavior               | Physical activity, diet, etc.                                              |
| 2   | Target user group             | Adults, children, etc.                                                     |
| 3   | Behavioral theory             | TTM, goal-setting theory, etc.                                              |
| 4   | Behavioral theory use type    | Informing design; guide evaluation strategies; selecting target users.     |
| 5   | Behavior change strategy      | BCT Taxonomy (v1) + (cooperation, competition, Recognition, virtual reward, and game integration). |
| 6   | Measurement                   | User experience (quantitative); user experience (qualitative); target behavior; user interaction (i.e., use frequency, use duration); behavioral factors (e.g., constructs from behavioral theories). |
| 7   | User experience Instrument    | SUS [12], AttrakDiff, etc. (Coding only when user experience is quantitatively measured.) |
| 8   | Intervention workflow         | Time-based; task-based; event-based. (Coding only when prompts/cues are used as a behavior change strategy.) |
| 9   | Intervention Characteristic   | See Table 4 for details.                                                   |

Table 4: The characteristics used in our coding and the explanations.

| No. | Characteristic   | Explanation                                                                 |
|-----|-----------------|-----------------------------------------------------------------------------|
| 1   | Medium          | The device for intervention delivery, e.g., PC and smartphone.              |
| 2   | Visualization   | Information visualization in software interfaces, e.g., progress bar and leaderboard. |
| 3   | Social support  | The social support type that the intervention can aid, e.g., social comparison and social recognition. See Table 5 for details. (Coding only when the intervention system provides social support function) |

4 Results and Findings

In this section, we report the results and findings of the systematic review based on the methods introduced in the previous section. We firstly show the trends of the paper amount in the perspectives of the target behavior and the paper type (see Table 2) over the research history of health behavior change in HCI. Then we select “compared intervention studies” (N=75) and analyze the research patterns in the views of measurements, user experience evaluation, the target behavior, the target user group, the application of behavioral theories, the use of behavior change strategies, and intervention characteristics.

4.1 Trends of Target Behaviors and Paper Types

We analyze the trends based on the papers after the title and abstract screening (N=648). Of the 48 target behaviors we found, five behaviors (i.e., physical activity, sleep, diet, smoking, and sedentary behavior) account for 73% in all the papers. As shown in Figure 4, physical activity remains the most popular target behavior over time and the corresponding papers keep growing in the last six years. The number of the papers targeting sedentary behavior also peaked in 2017. The paper amounts for sleep, diet, and others decreased in 2017 after 2-4 years increase. From the perspective of the target behavior, the decrease of papers about

3 http://attrakdiff.de
sleep, dietary behavior, and other behaviors except the ones listed in Figure 4 caused the drop in the overall paper count in 2017.

4.2 Patterns in the Selected Intervention Studies

4.2.1 Measurement & User Experience Evaluation

Differing from the target behavior as shown in Figure 4, the user interaction means the objective measure of how the users use the intervention system (e.g., the use frequency). In comparison with the user experience, the behavioral factors refer to the constructs (e.g., self-efficacy) influencing the behavior change process. The target behavior of users was measured in most of the studies (93%), as shown in Figure 6. More than half of the studies (59%) evaluated user experience quantitatively or qualitatively. The user interaction with the intervention system was measured in 34% of the studies. Only 20% of the studies accessed users’ behavioral factors, which is related to the usage of behavioral theories.

Figure 5 illustrates the change of the paper amount regarding the paper type over time. Most (55%) of the papers contain designing new intervention systems or methods for health behavior change. However, only about 25% of the developed systems or methods were evaluated by the intervention study with compared conditions. The “data mining” papers saw a drop in 2017, while the “survey” papers and the “interview” papers have been rising in the last three years. The drop in “data mining” and “design” papers mainly contributed to the overall decrease in 2017.

Although about 59% of the studies accessed the user experience, only 32% (24/75) of them evaluated the user experience with quantitative measurements. The system usability scale (SUS) was used in four studies [25,26,55,95], while the NASA-TLX [45] and the AttrakDiff [21] were used only once. The studies with game integration were more likely to measure users’ perceived enjoyment (e.g., [8,37,56]). One study [94] was conducted within a clinical trial, which used the Patient Reaction Assessment (PRA) questionnaire to measure users’ experience of the intervention. We did not find any specific scale to evaluate the user experience of interventions for health behavior change.

4.2.2 Target User Group & Behavior

As shown in Figure 7, the target user group in most studies was the adult (68%), while almost half of these studies used college
students and staff as the participants. Children, as the target user group, accounted for 15% in all studies. There is only one study targeting teenagers, while one study focused on young adults. From other aspects of the user group: five studies aimed at patients, three studies focused on the female, and one study only considered athletes. The reviewed studies are very unbalanced regarding the target user group.

4.2.3 Behavioral Theories

Among the 75 selected intervention studies, 32 studies (43%) explicitly described the use of behavioral theories. The transtheoretical model (TTM) was the most frequently used theory, which was adopted in eight papers. This result is in line with another systematic review by Orji and Moffatt [73]. The other behavioral theories adopted in the reviewed studies are listed in Figure 8.

![Figure 8: The distribution of the used behavioral theories. SRT refers to the self-regulation theory; HBM refers to the health belief model; IBM refers to the integrated behavioral model. The other acronyms can be found in the following content.](image)

Figure 9 illustrates how behavioral theories were used in the reviewed studies. The TTM was mainly used to select target users [18,19,35,40,45,50], as illustrated in [38]. In the case of using the TTM to inform the intervention design, different strategies were delivered according to the user’s stage of change [36,39]. The self-efficacy theory (SET) [4], the theory of planned behavior (TPB), the self-determination theory (SDT) [22], the Fogg’s behavior model [30], and the goal-setting theory (GST) [52] largely contributed to informing the intervention design.

Regarding the studies that did not utilize behavioral theories, we found that 29% (12 studies) focused on exergame and gamification (e.g., [82]), while 21% (9 studies) targeted children or teenagers (e.g., [86]). Behavioral theories might be useless in the case of the short game session (e.g., exergame). However, users’ adoption and engagement with health orientated game design could also be explained by behavioral theories. The work from Macvean and Robertson [55] indicated that children’s motivation of playing exergame would decrease over time and self-efficacy theory can predict and interpret the longitudinal physical activity patterns of children’s behavior change as well.

![Figure 9: Behavioral theories and the ways that they were used in the reviewed studies. I – informing design, G – guide evaluation strategies, S – selecting target users. Note that, in this alluvial graph, the relative sizes of the bars for each behavioral theory do not exactly represent their use frequency. In one study, a behavioral theory can be used for both informing design and guiding evaluation strategies.](image)

![Figure 10: The word cloud of behavior change strategies found in our reviewed intervention studies (N=75). The bigger the font is, the more frequently the strategy was used.](image)

4.2.4 Behavior Change Strategies

Among the reviewed studies, the most used behavior change strategies are self-monitoring of behavior, goal-setting (behavior), feedback on behavior, prompts/cues, and game integration (see Figure 10). In section 1.2, we have shown the cloud map of behavior change strategies coded from the papers listed on the website of BCT taxonomy. Those papers are mainly from journals of public health, behavioral science, and healthcare (e.g., BMC
public health\textsuperscript{3} and JMIR\textsuperscript{4}). In comparison with our reviewed papers, the researchers of those papers are more likely to use goal-setting (behavior), action planning, problem-solving, instruction on how to perform a behavior, and information about health consequences. This indicates the different use patterns of behavior change strategies between the HCI community and the community of public health, behavioral science, and healthcare.

We have shown the distribution of the target behavior in the papers of all the selected types (N=648) in Figure 4, where the papers targeting physical activity are much more than other types. Among the 75 full coded studies, the target behaviors are also unbalanced in quantity, and physical activity is still the most addressed behavior. Figure 11 illustrates the interaction of the top-4 target behaviors and behavior change strategies (in-group) in the reviewed studies. The alluvial graph indicates that a variety of behavior change strategies was used for all the target behaviors. One interesting finding is that almost all of the studies using game integration were designed for physical activity.

**Figure 11:** The top-4 target behaviors and the corresponding behavior change strategies groups in the reviewed studies. Note that, in this alluvial graph, the relative sizes of the bars for each target behavior do not exactly represent their frequency. Given the target behavior in one study, several strategies might be used.

### 4.2.5 Intervention Workflow

We found 16 out of 75 studies involving reminders (i.e., prompts/cue), including 9 event-based reminders [9,10,13,21,26,48,83,84], and 7 time-based reminders [7,32,44,66,75,85,94]. We did not find any task-based intervention workflow, according to the definition in the BIT model (i.e., the release of intervention elements are based on the user’s completion of prescribed intervention tasks [62]). Among the studies where the intervention system did not provide any scheduled reminders or prompts, we found a group of studies using always-on glanceable cues [5,19,35,78] to nudge users. For example, Gouveia and colleagues [35] designed watch faces of the smartwatch to provide real-time feedback about the user’s physical activity.

### 4.3 Characteristics of the Selected Intervention Studies

#### 4.3.1 Media

The media determine the information channel of the intervention. The mobile phone (including the smartphone and the functional phone) was used in most of the studies (44/75). The mobile phone, especially the smartphone, has become indispensable in our daily life. Therefore, the high adoption rate of the mobile phone is not surprising. The rest of the adopted media in the studies are listed in Figure 12. The web means that the study did not restrict users to use a mobile device or a PC. Except for the common devices (e.g., PC, the mobile phone, the fitness tracker), some new devices were created to solve specific problems. For example, the wearables for monitoring sitting poster [26] and augmented slider for supporting children’s learning process [56].

#### 4.3.2 Visualization

The visualization means how the intervention is presented to the users via the software interface. As shown in Figure 13, the plain text (e.g., SMS and notification), the progress bar, and the gamification interface were the most popular visualization methods. The others include the virtual agent, the timeline, the leaderboard, the reward sheet, the icon, the cartoon figure, the Emoji, and so on.

**Figure 12:** The media used in the reviewed studies. The unknown refers to the studies that did not explicitly mention the media. The wearable means the ones users can wear on clothes or shoes, rather than fitness trackers and smartwatches.

\textsuperscript{3} https://bmcpublichealth.biomedcentral.com/

\textsuperscript{4} http://www.jmir.org/
Figure 13: The word map of the visualization methods used in the reviewed studies. The bigger the font it, the more frequently the visualization method was used.

4.3.3 Social Support

We found 21 studies that provided the function of social support. The types of social support appeared in these studies are listed in Table 5. Some of the types are included in the BCT taxonomy [59] (e.g., social comparison and social incentive) and PSD principles [70] (e.g., social cooperation and social competition). However, our social support types and the explanations might be different from the definitions in the BCT taxonomy and PSD principles. Instead, we derived these social support types by analyzing the intervention descriptions in the reviewed studies.

Table 5: The social support types.

| No. | Social Support Type | Explanation |
|-----|---------------------|-------------|
| 1   | Social commitment   | It allows a user to make commitments within the intervention platform [66]. |
| 2   | Social sharing      | It allows users to see each other’s status, without aiming to compare with each other within the intervention platform [25,42]. |
| 3   | Social comparison   | It allows users to compare with each other within the intervention platform [16,18,28]. |
| 4   | Social competition  | It allows users to compete with each other within the intervention platform [31,37,68,95]. |
| 5   | Social communication| It allows users to communicate with each other within the intervention platform [11,18]. |
| 6   | Social incentive    | It allows users to encourage each other within the intervention platform [16,25,41,83]. |
| 7   | Social interaction  | It allows users to interact with each other with the intervention tool face to face [6,53]. |
| 8   | Social monitoring   | It allows other users to monitor a user’s behavior, but not vice versa [75,83,93]. |
| 9   | Social recognition  | It allows users to recognize their peers in public [43,78]. |

5 Discussion

We have reported our findings of the research trends and patterns of the research on health behavior change in the HCI community. These findings indicate several shortcomings and problems to be addressed in this research field:

1. The target behaviors mainly fell into physical activity, while some critical behaviors (e.g., sedentary behavior [91] and stress management [81]) were much less addressed.
2. The target users or study participants were mostly adults who were mostly college students and staff. We believe that more attention on the elderly is required in the aging society.
3. There is no standardized approaches or instruments for evaluating the user experience of intervention systems for health behavior change.
4. There is no standard to report the intervention study for health behavior change. The method we used to review the related papers provide an approach to reporting the relevant study. The study aspects that we suggest to report are shown in Table 3 and Table 4.

Following, we select six topics inspired by the reviewed studies to provide suggestions and opportunities for future studies. The first three topics are about users: considering the user’s behavior priority, categorizing target users from different perspectives, and leveraging users’ power of creativity and engagement. The other topics include longitudinal studies with game integration, cautions for socialization, and the applications of AI in health behavior change.

5.1 Users’ Behavior Priority

Although behavioral theories could be beneficial for the research on health behavior change in HCI, they are not without limitations. One of the limitations is that behavioral theories can explain only 20–30% of the total variance in a given health behavior [38]. From the reviewed papers, we noticed one factor that could collaboratively explain health behavior change. In the study by Rodgers and colleagues [77], they found that college students consciously prioritize academic success over a healthy sleeping pattern. This finding indicates the fact that an individual’s daily life is filled with various tasks and behaviors (e.g., academic success and healthy sleeping pattern), instead of only the target behavior of a given intervention study. People can fail to adhere to an action plan just because they need to do other actions with higher priority in their limited time. Systems that can support users to schedule their daily activity and fit the target behavior into their routine could be a solution to the difficulty caused by priority.

Therefore, we suggest that future intervention studies should consider the behavior priority of participants. For example, the efficacy of sedentary behavior interventions could relate to users’ work priority. Intervention designers should check if there are critical tasks or dues hindering users’ enactment of their plans to reduce their sedentary behavior.
5.2 Categorizing Target Users

An intervention may be valid only for a specific group of audience, and the lack of specification of users could hide the effectiveness in study results. For example, Lacroix and colleagues [46] found that positive linear relationship between goal difficulty and users’ performance only existed for inactive people, but not for active people. Therefore, categorizing the target users in meaningful ways could lead to a better understanding of the intervention efficacy. In Figure 9, we have shown that the transtheoretical model was often used to group participants into different stages of change and select the target users. Besides the stage of change, researchers have found other methods and perspectives to categorize target users. E.g., Wiafe and colleagues [92] proposed a model to classify users based on their current behavior, attitude, and levels of cognitive dissonance.

Users’ personality is also a potential way to categorize target users, e.g., the well-known Big Five personality traits [87]. As many health intervention studies have used gamification, the research on the personality of users (players) in games has drawn more attention [67]. Orji et al. [74] examined how different personalities respond to various persuasive strategies that are used in persuasive health games and gamified systems. Another study [72] showed that tailoring the game design to players’ personality type improved the effectiveness of the games in promoting positive attitudes, intention to change behavior, and self-efficacy. Our second suggestion is that future intervention could categorize target users not only based on the stage of change but also other factors (e.g., personality).

5.3 Leveraging Users’ Power

Researchers have started to explore and leverage the users’ creativity in health behavior change. Lee and colleagues [47] deployed a self-experiment design to support behavior change for improving participants’ sleep quality. In another study [75], a participatory design session was used after an intervention session for medication management among the elderly. Both of the studies proved the efficacy of user participation in the intervention design process.

In the study of Birk and Mandryk [10], a group of users was asked to customize their avatars to interact in a breathing exercise program. Compared to the control group with randomly assigned avatars, the customization group saw significantly less attrition and more sustained engagement through the 3-week study. In this study, customizing an avatar with its appearance and attributes required a minimum of 4-minute work of a participant. The effect of users’ participation can be explained not only from the perspective of customization but also from the view of IKEA effect [69,89]. The involvement of users’ effort in a product can increase their evaluation of the product.

Based on the evidence, we suggest that future intervention designers should take advantage of users’ participation and further explore the effect and user experience of participation.

5.4 Longitudinal Study with Game Integration

By game integration, we mean both exergames (i.e., interactive games that require players to invest significant physical effort as part of the gameplay [63]) and gamification (i.e., implementing the most common and enjoyable mechanics of video games in non-video game contexts) [61]. We extracted 15 studies with game integration and found that the study duration tended to be short, as shown in Figure 14. Macvean and Robertson [55] studied children’s physical activity patterns when using an exercise game on smartphones over seven weeks, which is the longest study on gamification among the 15 studies. Seven studies only reported their evaluation for one game session, which we counted as one day in Figure 14.

![Figure 14: The study duration of the studies with game integration.](image)

The distribution of the reviewed study durations is shown in Figure 15, where we can see the number of studies with the duration less than one day is 13. More than half of the short-term studies are about game integration. Therefore, more longitudinal studies in gamification are required, because the goal of health behavior change is to help users maintain a healthy lifestyle in the long term.

![Figure 15: The distribution of the reviewed study durations.](image)

5.5 Cautions for Socialization

Since every individual is part of the social network and mobile technologies keep changing our communication in the social network, it is vital to investigate how socialization can benefit health behavior change. Socialization for health behavior change means involving the support from private (e.g., families and friends) or public social networks in health interventions. We have listed the social support types in the review studies in Table 5.
Katule et al. targeted parent-child pairs to improve the parent’s physical activity via the child [41]. Chen and colleagues [15] found that collaborating with a buddy (dyads) to compete in a community can be effective to improve the daily steps of obese and diabetic patients. While studies have shown that social incentives have the potential to motivate people for health behavior change, some research showed cautions when deploying socialization. E.g., social interactions could be demotivating between dyads who did not know each other well [15]. The work of Munson et al. [66] showed that the prospect of public accountability might suppress the making of commitments which decreases social members’ motivation of obese adults.

More research on the requirements of socialization for different user groups is needed. For instance, how to apply social support to improve physical activity and dietary behavior of the elderly living along?

5.6 Embracing AI

Although recent applications of deep learning have boomed in many fields, its use for health behavior change is still in infancy. By AI in health behavior change, we refer to the system that adopts a social role in communicating with users for health behavior change. This definition emphasizes the interaction between the system and users. It excludes the system only providing functional support, e.g., food and ingredient recognition [14]. We found three systems following our definition of AI in health behavior change. Kamokoa and Mutlu used a humanoid robot to motivate users for physical activity in two interaction conditions [40]. Over a two-week study, although no significant difference was found in the users’ physical activity level, their intrinsic motivation was significantly improved. Interestingly, users’ willingness and perceived friendliness of the robot are both higher in the monologue condition (less interaction) than in the motivational interviewing condition (more interaction). This result might be due to the lack of fluency and error in speech recognition [40]. Another system by Lisetti and colleagues developed a virtual agent to deliver interventions on excessive alcohol consumption [51]. Their virtual agent can recognize users’ expressions and generate corresponding expressions to show empathic feedbacks. With empathic feedbacks, the virtual agent improved users’ attitude to the technology, intention to use, perceived enjoyment, and so on. Unlike the mentioned two systems with anthropomorphism, Kamphorst and colleagues developed an autonomous e-coaching system to deliver intervention messages to promote more stairs taking according to the problematic constructs for behavior change of users in real-time [39]. A month-long evaluation study showed that the intelligent e-coaching system could better support health behavior change.

The initial results of applying AI technology implicate the venues of research on health behavior change in HCI: natural language based intervention [40,51], emotion enabled intervention [27,51], and computational intervention [39].

Several limitations emerged during the systematic review. The search was conducted only in the ACM digital library, so the reviewed papers did not include all the related work in the HCI community. This might lead to bias in our results. We only searched the authors’ keywords to extract papers, which may also lead to missing some related papers. No paper explicitly reported the intervention strategies based on the taxonomy of behavior change techniques (BCTs). The coding is based on the authors’ understanding of the material provided on the website of BCTs taxonomy⁵, which might introduce bias to our analysis.

7 Conclusion

Through a systematic review of the research on health behavior change in the HCI community, this paper shows the research trends in the perspectives of the target behavior and paper types over the research history (N=648). Based on the selected intervention studies (N=75), it also analyzes the research patterns in the views of measurements, user experience evaluation, the target behavior, the target user group, the use of behavioral theories, the use of behavior change strategies, and intervention characteristics. The results show that physical activity was the most targeted behavior over time, and the related research keeps growing in recent years. Other behaviors (e.g. sleep, dietary behavior, smoking, and sedentary behavior) increasingly draw more attention with slight fluctuations. Studies using interviews or surveys continue to increase, while research on data mining and designing new intervention systems or methods dropped in 2017. Among the 75 intervention studies with compared conditions, only 32% of the studies quantitatively evaluated the user experience. The SUS, the NASA-TLX, and the AttrakDiff were used in the reviewed studies, while no standardized method to assess the user experience of intervention studies for health behavior change was found. Most of the target users in these studies were adults. There were 32 out of 75 studies explicitly reporting the use of behavioral theory, and the most used one is the transtheoretical model. A variety of behavior change strategies were used in the reviewed studies, while the most frequently used ones include self-monitoring of behavior, goal-setting (behavior), feedback on behavior, prompts/cues, and game integration. Almost all the studies with game integration were designed for physical activity. The mobile phone was the most popular medium to deliver interventions. The plain text, the progress bar, and the gamification interface were the top-3 visualization methods to provide information to the user. Regarding social support, we found nine use cases among the reviewed studies. Based on these findings, we discuss the shortcomings and problems to be addressed: unbalanced target behaviors, unbalanced target user groups, the lack of standardized evaluation methods for user experience, and the lack of standards to report intervention studies for health behavior change in HCI.

Finally, we provide suggestions and opportunities for the future research in the field of health behavior change in HCI. We suggest

⁵ http://www.bct-taxonomy.com/dashboard
considering users’ behavior priority and the ways to categorize target users when recruiting the study participants. We also point out the lack of longitudinal studies for game-integrated systems and the cautions for socialization-engaged systems. Also, we show how AI technologies have been used for health behavior change and implicate the research venues of AI in this field.

Responding to the trend of decrease in the related paper amount from the HCI community, we believe it is a temporary phenomenon. According to the findings and analysis in this paper, there are many unexplored research questions and opportunities in health behavior change for HCI researchers.

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