Keep Moving! A Systematic Review of App-Based Behavior Change Techniques and Visualizations for Promoting Everyday Physical Activity

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Abstract. Health apps are supposed to support fighting sedentary lifestyles and, consequently, a variety of chronic diseases. For promoting physical activity in a sustained manner, these apps and corresponding research draw upon a variety of behavior change techniques and visualizations. To provide a structured overview of recent approaches and identify research gaps, we conducted a systematic literature review of empirical research works on app-based approaches for promoting everyday physical activity. In the 42 relevant studies identified, we thoroughly analyzed the applied behavior change techniques and in-app visualization types. We found a recent emphasis on feedback and monitoring as well as goal setting techniques, while the application of others such as informing about health consequences or shaping the user's knowledge are applied only in rare cases. The range of visualization types is limited. Traditional charts and gamified illustrations turned out to be predominant. However, empirical research on alternative approaches such as innovative chart visualizations is scarce.

Keywords: Mobile Health, Behavior Change, Literature Review.

Introduction

Insufficient physical activity (PA) is a well-known risk factor for a widening variety of chronic diseases, including cardiovascular disease, obesity, diabetes mellitus and others. The global prevalence of insufficient PA is about 28%, for high-income countries even 37% [19]. Among adolescents globally more than 80% of students aged 11-17 years were insufficiently physically active (according to recent PA guidelines [20]). It is a global priority to encourage people engaging in PA and reduce the burden of non-communicable disease.

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The usage of mobile health apps on smartphones seems to be a promising approach to tackle this challenge. Health apps (HA) can inform the users about the importance of PA and its health relations, track their movements easily using built-in and external sensors and compare the numbers with international health recommendations to stay on track. Despite the increasing numbers of HA in the app stores, though, it seems that there is just modest evidence about their effectiveness and efficacy in improving health behaviors or health outcomes [32, 40, 49].

Providing knowledge alone to let people reflect upon and make beneficial decisions based on rationale is often not working. This information-centered approach can be supplemented with behavior change techniques (BCTs) or the concept of nudging to support users to improve their PA. Nudging is a form of choice architecture, that helps to change people's behavior in a predictable way to their advantage. The design of the choice environment in which the information is presented can also influence the outcome [56].

While several related prior works aimed at overviewing the large number of nudging theories, studies, and applications in the health domain, a systematic review of digital behavior change interventions for promoting PA from an HCI perspective is missing. For example, Forberger et al. [17] gave an overview of the scope of interventions using choice architecture techniques to promote physical activity with a focus on prompts at public locations. Laiou et al. [31] systematically appraised the evidence on nudging interventions with an emphasis on healthy diet interventions. Bondaronek et al. [4] reviewed nudging mechanisms for PA of popular publicly available PA apps within an overall quality evaluation.

In contrast, in our work we aim to survey and critically reflect on the existing body of scientific knowledge on smartphone and wearable-based behavior change interventions targeting PA from an HCI perspective. We set focus on everyday life PA such as walking and jogging due to its low-threshold integration without specific equipment and its location independence. We conducted a thorough systematic literature review to identify respective BCTs and HCI-related insights.

The contribution of our work consists of an overview of studies with focus on digital health intervention on PA and the included BCTs as well as the implemented visualization types. Based on these findings we draw conclusions and identify possible future research on mobile interventions based on BCTs for promoting everyday PA.

Method

In the following, we describe the process of our systematic review in detail. Figure 1 provides an overview of the study selection process.

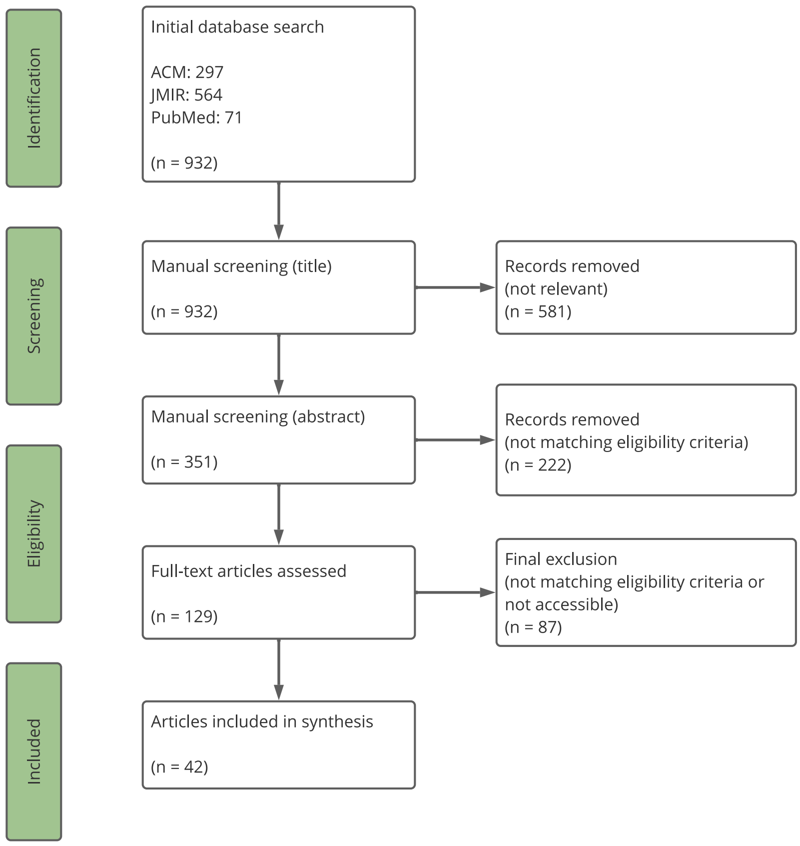

Fig. 1. Flow diagram of the study selection process

Data Sources and Search Strategy

Since relevant research is published in both computer science- and medicine-related conferences and journals, our scientific sources consulted include the online literature databases of ACM, PubMed, and JMIR Publications. As search term (within the title, abstract, and keywords) we used

- *physical activity*
- AND *smartphone/mobile phone/mobile health/mHealth/app/apps/mobile app*
- AND *behavior change/behaviour change/behavioral change/behavioural change/nudging/nudge*

For each literature database, the syntax of this pseudo search term was adapted to the database's specific requirements. Further search parameters that were manually applied through respective search settings were restrictions regarding the publication year (2017-2021) and the publication language (English).

Data Cleansing and Screening

The three result lists were exported and compiled into one spreadsheet for collaborative processing. For each of the 932 entries, the spreadsheet contained the publication's title, abstract, keywords, author(s), and year. Further information included the publication venue, type (conference/journal), publisher, ISBN and DOI. As expected, we did not identify any duplicates (checked by the publications' DOIs), since publications were searched and retrieved from three different publishers' databases.

During the subsequent screening process, two researchers applied an extensive set of eligibility criteria to further specify the list of relevant publications. We explicitly focused on peer-reviewed primary studies that (1) used a smartphone app in an intervention to promote PA or reduce sedentary behavior (SB), (2) included one or more BCTs, and (3) regarding the design, we included empirical studies, like randomized controlled trials (RCT), cross-sectional and longitudinal observational studies, pre- and post-design studies and experimental field trials.

The accepted units of measurements for the PA related outcomes were steps, active time, time in moderate to vigorous physical activity (MVPA), gait speed, burned calories, climbed stairs or floors, traveled distance, and METs (Metabolic Equivalent of Task).

Inclusion Criteria of Studies

- Interventions to promote measurable everyday PA (walking, running, climbing stairs or floors, etc.).
- Interventions using smartphones, smartwatches, smart bands, other types of activity trackers, or wireless transmitters (like BT-beacons).
- Target groups for the study include healthy populations of adolescents, adults, and older adults.
- The intervention must include any form of BCT to promote PA or reduce SB.
- The effectiveness of the intervention must be measured/discussed.

Exclusion Criteria of Studies

We excluded non-experimental study designs such as case studies, conceptual papers, literature reviews or theoretical views, opinion papers and studies reporting prevalence or trend data.

- We excluded interventions based on activities that require additional equipment like treadmills, steppers, mountain climbers, bicycles etc.
- We excluded interventions relying on additional monitoring equipment like chest straps, ECGs, smart shoes, IoT devices etc.
- Activities that require specific locations (swimming etc.) or strength exercises (bodyweight exercises, weightlifting etc.) were also an exclusion criterion.
- We excluded sick populations, patients during treatments and women during pregnancy as well as kids up to 12 years.

- Combined interventions like PA with sleep, nutrition, or mental aspects (like mood or stress) were excluded as well.

Data Analysis

After the screening process, 42 studies were considered relevant for our review and included for in-detail analysis. Figure 2 shows the number of publications for the five years considered. Relevant research per year increased from 6 publications in 2017 to 12 publications in 2021. The works include a broad range of empirical studies, e.g., with sample sizes ranging from 6 [7] to 6 million participants [1] and study durations between one week [43] and five years [1].

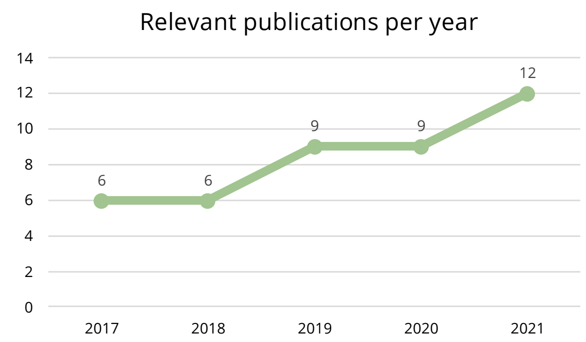

Fig. 2. Number of relevant publications per year.

In a thorough analysis of these studies, we identified BCTs and visualization types. BCTs were coded according to the Behavior Change Techniques Taxonomy 1 (BCTTv1, [39]). If BCTs were related to other frameworks or taxonomies (e.g., CALO-RE, [38]) or did not match the naming convention of our selected taxonomy, we translated the behavior intervention to the best matching replacement. BCTs which did not directly target PA were omitted. Visualization categories were created in an inductive coding approach.

Results

This section presents the results of our analysis of the included publications. We report on the different BCTs and visualization techniques applied.

Behavior Change Techniques

Table 1 shows in detail BCTTv1 (sub)categories [39] addressed by the publications reviewed. Figure 3 depicts the numbers of applications of respective BCTs in the reviewed research studies on everyday PA interventions. Each study combined several different BCTs. The number of BCTs per intervention ranged from 2 to 11, while on average 5 to 6 different BCTs were combined in one intervention.

Table 1. BCT (sub)categories (Michie et al ref) addressed by the publications reviewed

BCT (sub)category	Publications
1 Goals and planning	
1.1 Goal setting (behavior)	[2, 3, 5, 7, 8, 9, 10, 12, 13, 14, 16, 18, 22, 23, 24, 25, 26, 27, 28, 29, 30, 33, 34, 36, 37, 41, 43, 44, 45, 46, 47, 50, 51, 52, 55, 58]
1.2 Problem solving	[12, 36, 46, 50]
1.4 Action Planning	[12, 23, 28, 36, 44, 50, 52, 55]
1.5 Review behavior goal(s)	[14, 36, 50]
1.6 Discrepancy between current behavior and goal	[2, 36, 51]
1.9 Commitment	[7, 36]
2 Feedback and monitoring	
2.1 Monitoring behavior by others without feedback	[1, 3, 21, 22, 29, 57]
2.2 Feedback on behavior	[1, 2, 5, 8, 9, 10, 12, 13, 16, 22, 23, 25, 25, 27, 30, 33, 36, 37, 41, 42, 44, 48, 51, 58]
2.3 Self-monitoring behavior	[1, 2, 3, 5, 7, 8, 9, 10, 12, 13, 14, 15, 16, 18, 21, 22, 23, 24, 25, 25, 26, 27, 28, 29, 30, 33, 34, 36, 37, 41, 42, 43, 44, 45, 46, 47, 48, 50, 51, 55, 57, 58]
3 Social support	
3.1 Social support (unspecified)	[5, 13, 14, 21, 22, 23, 24, 29, 37, 47, 50]
3.2 Social support (practical)	[16, 25, 26, 33, 43, 45, 46, 52, 57]
3.3 Social support (emotional)	[16, 25, 26, 33, 43, 45, 46, 52, 57]
4 Shaping knowledge	
4.1 Instruction on how to per-form a behavior	[5, 12, 14, 22, 26, 29, 46, 51, 55]
6 Comparison of behavior	
6.2 Social comparison	[1, 3, 13, 16, 23, 24, 33, 37, 43, 44, 45, 46]
7 Associations	
7.1 Prompts/cues	[7, 9, 13, 25, 26, 27, 28, 30, 33, 36, 37, 44, 46, 48, 55, 57]
10 Reward and threat	
10.1 Material incentive (behavior)	[15, 22, 30, 34, 41, 44]

10.2 Material reward (behavior)	[9, 27, 44]
10.3 Non-specific reward	[3, 10, 13, 33, 34, 37, 43, 46, 47, 57]
12 Antecedents	
12.5 Adding objects to the environment	[7, 33, 47]
13 Identity	
13.1 Identification of self as role model	[16, 22, 23, 24, 37, 45, 46, 52]

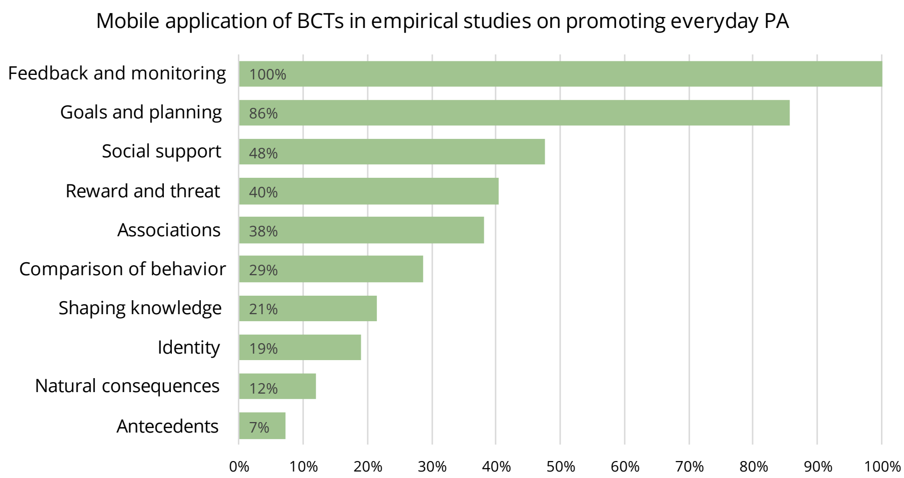

Fig. 3. The relative usage of BCT techniques in empirical studies on apps for increasing everyday PA shows an emphasis on “goals and planning” and “feedback and monitoring” techniques. Each study combined several different BCTs.

We found a clear emphasis on the two strategies “feedback and monitoring” and “goals and planning”. “Feedback and monitoring” techniques were used in each of the 42 studies reviewed. Almost every mHealth intervention provides self-monitoring for the users’ behavior, e.g., via app or smartwatch. In many cases monitoring is also performed by others with feedback (by staff or buddies) or without feedback [3, 21]. “Goals and planning” features were found in 36 studies (86%). Goals related to physical activity and condition include both predefined or individual goals stated by the app (i.e., determined by the app provider) or self-set goals. These goals explicitly address the user’s behavior change, e.g., by targeting a specific number of steps or time amount of MVPA. In contrast, gamified approaches make use of game-related goals, thus, indirectly initiating the user’s behavior change.

The third-ranked technique “social support” was only applied by 20 of the 42 studies (48%). Typical examples include encouragements by team members or buddies via in-app communication or by sending virtual approval, like high fives or virtual gifts such as digital flowers to support the user in achieving his or her activity goals. Besides these solely digital features, further “social support” implementations bridge the digital and the analog world, e.g., by enabling to organize running groups within the app [24]. 17 studies (40%) applied the “reward and threat” technique: They featured either incentives (before the PA as a prospect) or rewards (after the PA). We found both implementations of analog material rewards, e.g., money and vouchers, and digital ones, e.g., virtual badges and trophies.

16 of the studies reviewed (38%) made use of “associations”, i.e., prompts and cues nudging users to perform everyday PA. In most cases, this is accomplished through context-sensitive push notifications. E.g., due to the device’s current location or the current time of day, the user is reminded of pending PA *(“You haven’t yet been active for 30 minutes today!”*) and prompted to perform PA *(“Take 2000 steps in the next 20 minutes!”*).

While popular in various sports tracking apps, the “comparisons of behavior” technique turned out to be less investigated in HA studies on everyday PA. Only 12 of the 42 publications (29%) included typical social comparison features such as leader boards or notifications on buddies’ recent PA. 9 publications (21%) included “shaping knowledge” features by investigating advise, training, or explanations on how support behavior change regarding everyday physical activity. Some of the examples include instructions on how to correctly perform heart rate measurements, hints on suitable running equipment, or suggestions regarding fitness exercises. Such information was provided through different channels, e.g., through notifications, text messages, or via telephone-based lifestyle coaching.

In the group “identity” the BCT “identification of self as role model” was implemented in 8 studies (19%), e.g., when group members were encouraged to be the team captain and to support group interaction and encouragement [16].

“Natural consequences” of sufficient PA (or SB, on the contrary) were communicated within 5 research works (12%). This includes information about health consequences such as being less/more susceptible to diseases or live longer/shorter due to specific behaviors.

A few studies made use of “antecedents” by adding (virtual) objects to the environment. This approach was in use for some GPS-based gamified interventions to motivate users to reach a specific location, where the objects can be discovered or collected [7, 47].

Visualization Types

Besides the actual usage of existing BCTs, we were further interested in how relevant information was visualized for the user. Table 2 presents the different visualization types identified in our literature body in conjunction with the respective literature sources.

Figure 4 depicts the relative usage of different visualization types in recent research on health apps for promoting everyday PA. Graphs turned out to be the most frequently used visualization type in our review. In 23 publications (55%), bar, line, and ring charts were applied to either present key metrics of the user's (or buddies') physical activities over recent days or weeks or to indicate active time (MVPA). Only 2 publications (5%) showed respective data by numbers only.

Table 2. Different visualization types identified in the literature body.

Visualization type	Publications
Graphs	[2, 3, 10, 12, 15, 16, 21, 22, 27, 28, 30, 33, 36, 37, 41, 42, 43, 45, 50, 51, 55, 57, 58]
Numbers only	[8, 9]
Gamified	[3, 7, 13, 16, 23, 33, 37, 43, 47, 57]
Activity feed (timeline)	[1, 7, 10, 13]
Tables/rankings	[13, 21, 22, 23, 24, 33, 37]

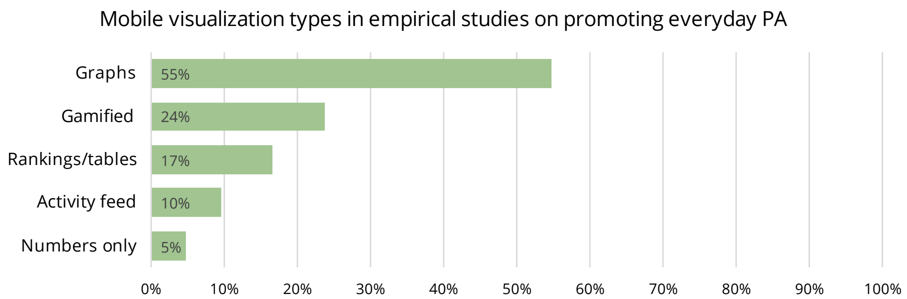

Fig. 4. The relative usage of visualization types in empirical studies on apps for promoting everyday PA: traditional graphs and gamified illustrations are predominant.

Beyond graph-style and numbers-only representations of PA performance data, we found 10 gamified visualizations (24%) in a broad range of implementations. Typical examples are virtual trophies and badges for specific achievements. Advanced concepts include collecting virtual playing cards which can be traded with other users or chasing virtual objects anchored at real-world locations.

7 of the 42 research works (17%) used rankings to directly compare the user's PA performance with those of his or her buddies or competitive teams. Variations include the performance metrics (e.g., steps, time spent, points achieved) as well as the compared group (within a specified team of buddies or global). Finally, only 4 studies (10%) investigated app prototypes with activity feeds. These social media-like news streams either show a scrollable list of the users' own or the buddies' activities.

In 8 publications (19%) we did not find any information on the visualization type applied in the respective study.

Discussion

In the following, we reflect on the results of our literature review. We discuss the usage of BCTs and visualization types in recent research on interventions to promote everyday PA, particularly regarding their efficiency.

Behavior Change Techniques

The most common BCTs used in interventions are goal setting (behavior), feedback on behavior and self-monitoring of behavior. The combination of those three BCTs within one intervention study was also the most common (e.g., [2, 8, 58]. However, some promising goal setting BCTs like problem solving [12, 50] or reviewing behavior goals (and adapting behavior change strategies) [14, 36, 50] were only found in a few interventions and seem to be used rarely in most modern PA promoting health apps and digital health interventions.

Social support in different variations seem to be promising BCTs to promote PA [16, 21, 22, 26, 43]. Several studies focused on examining the effects of peer groups or teams which tried to reach a common PA goal. Physical contact (instead of online contacts) or proximity of location [45] as well as higher frequency of communication [21] seem to be supporting factors. Exposing data about the PA to the public also significantly increased the effort and changed behavior compared to self-monitoring [3].

Monetary incentives and rewards [15, 27, 30] and virtual rewards (e.g., trophies or badges) [10, 37] seem to be an acceptable strategy to trigger behavior change. It motivates users to reach artificial daily step goals, whereby most users cease their PA efforts after the incentivized goals are reached [27, 34]. However, incentives and rewards can also have negative effects in the long-term on intrinsic motivation of the participants, as shown by [9].

It is common to deliver prompts, feedback and reports relative to goal achievements (e.g., a percentage of the step goal) or at specific times (e.g., [9]). However, some studies implement just-in-time-adaptive-interventions (JITAI), which are a promising alternative approach to deliver nudges and provide BCTs within the most appropriate context and when the user would be receptive to it [28, 41, 48].

Some BCTs are incorporated via push notification to either prompt behavior, inform about reached goals or provide information like health facts. However, studies show that there is an attrition effect if the message frequency is too high, or there is already a high emergence of other notifications (e.g., from social media like Facebook, Instagram, Snapchat, and others). This effect is also apparent if there is too much repetition content-wise or just because of lack of interest [51].

The most common BCTs used in interventions are goal setting (behavior), feedback on behavior and self-monitoring of behavior. The combination of those 3 BCTs within one intervention study was also the most common (e.g., [2, 8, 58]). Regarding the combination of different BCTs, it seems noteworthy that a higher number of BCTs used in interventions does not necessarily provide better results or stronger effects. There were studies with only a few BCTs (e.g., [15, 28, 58]) with significant effects on PA and studies with higher numbers of used BCTs without significant effects on PA (e.g., [46]).

Visualization Types

Our analysis showed a strong emphasis on graphs for visualizing performance and key metrics in health apps on everyday PA. In most cases, very basic traditional chart types such as bar, line, and ring charts are used; in most cases in combination with static performance goals. While most users probably are familiar with these traditional chart types and thus this decision is reasonable from a usability perspective, we see potential for future research in specialized chart visualizations considering adaptive goals.

(Self-)Moderated or adaptive activity goals seem to be more accepted and motivating than static goals (e.g., [58]). Especially the widespread 10,000 steps goal, which originated in marketing, has been described by some authors as detrimental to motivation. However, it is frequently used in our research body [3, 8, 34, 58]. To follow current health recommendations and support motivation, time-based qualitative activity goals or intensity goals (MVPA) should be considered, as pointed out in some of the studies (e.g., [18, 29, 46, 50]).

A related visualization approach is *Movilio* [54], which applies a combination of bar charts for visualizing a continuous floating 7-day activity goal. Users can shift the visualized period forth and back to see how the activities of different intensities influence the PA necessary to achieve the desired health benefits. The app calculates the effort still required to reach the goal depending on the past activities. However, this novel visualization approach is not empirically validated so far.

Despite various attempts to keep users engaged, e.g., through gamified visualizations, the drop-off of PA tracking is a general problem seen in many studies, especially with longer duration. For example [34] with its big sample of 140,000 participants shows a drop to 54% after one month and only 9% of all participants remaining after 6 months of tracking. Several other studies report on drop-off rates between 30% and 50% [12, 25, 37, 49].

Finally, alternative visualization types beyond charts seem under-explored for promoting everyday PA through mobile apps. While we found some examples of creative visualizations such as avatars or a blooming garden in prior work (e.g., [11, 35, 53]), no comparable visualization approaches were found in our body of literature.

Limitations

Through our systematic literature review, we aimed at providing an overview of recent research efforts on promoting everyday PA through health apps. In consequence, we limited our search to articles published within the past five years. We queried three major scientific databases from both the computer science and medicine domain. Still, additional publisher databases and search engines for scientific articles might provide further relevant research works. During the coding process of the documents, we captured BCTs that were explicitly described by the authors. In cases, where the descriptions might have lacked relevant details, a respective BCT could have been missed.

Conclusion and Outlook

In this review we gave an overview of recent empirical studies with mobile health interventions to promote PA based on BCTs. Our findings show that there is an emphasis on feedback and monitoring as well as goal setting techniques, while the application of other techniques such as informing about health consequences or shaping the user's knowledge are applied only in rare cases. The range of visualization types that is used to communicate performance metrics and goals is limited. Traditional charts and gamified illustrations turned out to be predominant while custom alternative approaches are scarce.

Due to heterogeneity of study and intervention types, target populations and BCT implementations there is no clear evidence about consistent patterns of superior strategies or better performing combinations of BCTs. Interaction and interdependency of multicomponent interventions remain unclear.

None of the studies made a specific evaluation of BCT usage or quantified BCT-related app features (e.g., how frequently or how long specific app features are activated or recalled). Only one study evaluated efficacy of single BCTs and combinations [50] and concluded that different combinations of BCTs may be effective to promote PA and reduce SB. Future work could focus more on comparison of single BCTs and combinations thereof to provide evidence for BCTs with more potential and those with less. The effects of interventions did not increase with higher number of implemented BCTs. Interventions could therefore benefit from less complex implementations of a few effective BCTs to promote PA.

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