Behavior Change Support Systems from a Self-Control Theory Perspective: A Systematic Literature Review Across Domains

Jan M. Enkmann[1,*]

[1]Hasso Plattner Institute, University of Potsdam, Prof.-Dr.-Helmert-Str. 2-3, 14482 Potsdam, Germany

Abstract

Behavior Change Support Systems (BCSS) are software systems delivering transparent, non-coercive interventions for behavior change - helping their users achieve their own long-term behavioral goals such as eating more healthily or exercising more often. From a psychological perspective, this can be viewed as assisting users' self-control - the ability to align behaviors with long-term goals while resisting immediate temptations and distractions. This systematic literature review synthesizes 49 studies testing 72 digital BCSS features through the lens of self-control theory - allowing for a direct comparison of their effectiveness based on the strategies they use to assist self-regulatory processes. Results show that situational strategies (assistance in modifying the choice environment) are the most promising approach while cognitive strategies (changing mental states) are particularly effective when prompting users to make concrete action plans. Training-based strategies (building self-control capacity) show limited generalizability beyond the concrete task being trained. Six propositions for BCSS design and research are derived. Adopting a self-control perspective allows for the systematic comparison of interventions across behavioral domains—from reducing screen time to improving dietary choices—and facilitates transfer of effective design strategies.

Keywords

Self-Control, Cognitive Interventions, Situational Interventions, Training, Systematic Literature Review

1. Introduction

The use of digital technology to assist individuals in changing their own behavior — such as making healthier food choices or reducing screen time — has garnered significant interest across disciplines such as behavioral economics, psychology, Human-Computer-Interaction (HCI), and Information Systems (IS).

The IS field has extensively researched digital behavior change interventions through two main lenses. First, IS adopted the concept of nudging from behavioral economics—the deliberate design of choice architecture to steer decisions without regulations or financial incentives [1]. IS has applied such nudges to online environments or implemented them into apps such as to steer decisions towards healthier or more sustainable behaviors [2]. However, digital nudges have been criticized for their paternalistic nature due to concerns about potential misuse for manipulative purposes [3].

Second, a related stream has researched Behavior Change Support Systems (BCSS) - persuasive socio-technical information systems "designed to form, alter or reinforce attitudes, behaviors or an act of complying without using deception, coercion or inducements." [4]. Over more than a decade of research, the BCSS community has developed rich design frameworks - such as the Persuasive Systems Design (PSD) model - that describes how system features such as self-monitoring, reminders, feedback, and rewards can be used to influence behavior [5]. While persuasive strategies targeting behavior change ("B-change" [5]) often overlap with those described in the nudging literature (i.e., behavioral feedback from self-monitoring or reminders), BCSS are deliberately supportive and self-deployed by definition, emphasizing "autogenous approaches in which people use information technology to change

BCSS 2026: The 14th International Workshop on Behavior Change Support Systems, March 10, 2026, Hakodate, Japan
*Corresponding author.
jan.enkmann@hpi.de (J. M. Enkmann)
0009-0000-2889-5107 (J. M. Enkmann)

their own attitudes or behaviors through building upon their own motivation or goal" [5, p. 3]. Although plenty of research has described designs and empirical evaluations especially for BCSS primary task support features, recent reviews did not evaluate their effectiveness systematically. Beyond the BCSS community, reviews and meta-analyses have focused on specific outcome domains (i.e., digital device use management, see [6]), have not focused on digital interventions (i.e., [7]), or were entirely narrative in nature (i.e., [8]). Furthermore, the BCSS community has highlighted open challenges such as an over-concentration on specific domains (especially health), limited cross-domain generalization, and a lack of integrative perspectives that connect persuasive features to underlying psychological mechanisms [9, 10].

Here, building on the interdisciplinary nature of the BCSS literature [9, 10], a qualitative systematic literature review [11] was conducted on (quasi-)experimental studies evaluating the effectiveness of digital BCSS features. In the attempt to integrate different literature streams, this study leverages psychological theories on self-control - the ability to align daily actions with explicit long-term goals (i.e., eating more healthily or reducing one's own social media consumption) while forgoing more immediate temptations when conflicting with this goal (i.e., ingesting a tasty cake or opening Instagram) [12]. Many BCSS target behaviors that inherently require resisting short-term impulses in favor of long-term goals, yet existing frameworks primarily describe persuasive systems at the level of design features or outcomes (e.g., compliance, behavior change, attitude change), rather than at the level of the self-regulatory mechanisms they seek to support.

Hence, regarding BCSS from the perspective of self-control aims to make two contributions to the BCSS community: First, searching for literature from the perspective of self-control theory and using corresponding keywords provides a cross-domain overview of digitally applied BCSS - from managing digital behaviors such as controlling online shopping and limiting digital device use to providing support with adhering to a healthy diet or increasing physical activity. Second, the lens of self-control theory allows insights into the psychological mechanisms behind BCSS, categorizing them into cognitive (e.g., changing mental states), situational (e.g., reducing the need for self-control by altering the choice environment), and training-based interventions (e.g., self-control capacity training). Rather than grounding each intervention approach in a separate psychological theory (i.e., see discussions of psychological theories for BCSS in [4]), the self-control perspective provides a unifying theoretical perspective applying to a large range of BCSS intervention strategies allowing for a better understanding of how core mechanistic features of BCSS contribute to the desired behavior change and for comparing their effectiveness.

The review synthesizes evidence from 49 studies testing 72 distinct digital BCSS features targeting self-control for behavior change (B-change). The intervention strategies as well as their delivery methods (e.g., smartphone apps, web platforms) and target outcome domains (i.e., from diet to safer driving) and their effectiveness are described to derive propositions for both, practitioners and future research of BCSS.

2. Theoretical Background

2.1. Persuasive Systems and Behavior Change Support Systems

Persuasive systems - and Behavior Change Support Systems (BCSS) in particular - are digital interventions designed to shape users' attitudes and behaviors through software-mediated influence [4]. A cornerstone in this field is the Persuasive Systems Design (PSD) model developed by Oinas-Kukkonen and colleagues, which provides a systematic framework for analyzing and building persuasive interventions [4]. The PSD model enumerates 28 design principles for persuasive system content and functionality, grouped into four categories: primary task support, dialogue support, system credibility, and social support. This framework has become central in BCSS research, offering a methodical way to assess persuasive features of information systems and guiding designers in incorporating elements like goal-setting, feedback, credibility, and social interaction to effectively support behavior change [10].

2.2. The Phenomenology and Theories of Self-Control

Self-control — the ability to align everyday behavior with long-term goals despite competing short-term temptations or distractions - is fundamental to many outcomes that BCSS seek to support - such as helping users stick to a diet, reduce screen time, or increase physical activity.

Despite the intuitive nature of self-control, defining it scientifically has proven difficult, leading to a wide variety of terms that describe overlapping but distinct concepts - from self-regulation to willpower and mental effort to cognitive and executive control [13]. Furthermore, several theoretical frameworks have been proposed to explain the mechanisms underlying self-control. One early theory is the strength model of self-control, which compares self-control to a muscle—being depleted when used too extensively but trainable over time [14]. Another influential framework is the dual-system theory, which conceptualizes self-control as an interaction between two competing modes of cognitive processing: System 1 (fast, intuitive, emotional) and System 2 (slow, deliberate, rational) [15]. In this view, self-control is the process of overriding impulsive System 1 responses with more deliberate System 2 evaluations [16].

In this article, we adopt a broad and outcome-oriented definition provided by Duckworth et al. [12], such that self-control is "any voluntary action intended to advance more enduringly valued goals over momentarily more alluring alternatives" (p. 49). Moreover, this requires the subjectively effortful activation of additional cognitive resources like attention reallocation and working memory load to choose between competing behavioral options [17] – one typically aligned with long-term benefits (e.g., sustainable health-benefits from exercising) and the other offering immediate gratification but less favorable long-term consequences (e.g., avoidance of effort by staying on the couch). This definition captures the core challenge that BCSS address—supporting users in bridging the gap between what they may prefer in the moment and what they value in the long run.

2.3. Behavioral Interventions for Self-Control Assistance

Although self-control has traditionally been viewed as a stable personality trait predictive of health, wealth, and academic success [18], recent research demonstrates that it can be influenced by targeted interventions [19].

Duckworth and colleagues categorize a large set of such self-control interventions along two dimensions: (1) who deploys them and (2) their mechanistic approach [7]. Other-deployed interventions are designed by external actors (i.e., a user interface designer) to steer choices supposedly beneficial for the target population, paralleling traditional paternalistic nudging techniques. Self-deployed interventions, on the other hand, are adopted by users themselves and are often inherently transparent - such as systems that assist in goal setting or progress tracking - paralleling the philosophy of BCSS [5]. Mechanistically, Duckworth and colleagues differentiate between cognitive and situational interventions. Cognitive interventions aim to "change the way they [people] think, making long-term choices more appealing or actionable and short-term temptations less so" [7, p. 108] - such as by means of goal setting support or instructions to mentally simulate future outcomes. Situational interventions, on the other hand, help individuals with the "deliberate change of his or her environment to create incentives, obstructions, and affordances favoring long-term goals over short-term temptations" [7, p. 106] - such as installing an app that blocks specific social media apps at certain times of the day.

Beyond this framework, a third approach aims to increase self-control through training - either as a general mental capacity or by targeting underlying executive functions such as working memory, attention, or inhibitory control. Neuroscientific studies have shown some potential for such trainings [20, 21]. For example, Kehr and colleagues designed and evaluated "The Chocolate Machine", a physical persuasive system device where users had to repeatedly resist a tempting chocolate reward in order to strengthen their self-control capacity [22]. The results showed that not only the ability to resist chocolate improved over time but that this effect also generalized to higher self-control in general, operationalized by longer endurance in effortful tasks. However, more research is needed into the generalizability of training individual executive functions to self-control more broadly and across contexts [21].

In the digital realm, self-control interventions have often been researched within specific outcome domains such as health or digital wellbeing. For example, Lyngs et al. [23] reviewed Digital Self-Control Tools - apps or browser extensions that help users manage screen time. While these tools have been shown to be effective in reducing digital device use [6], no comprehensive systematic review has examined how such self-deployed digital interventions can be applied across behavioral domains.

2.4. BCSS in the light of Self-Control Theories

From Duckworth and colleagues' taxonomy [7], BCSS can be understood as self-deployed self-control interventions - voluntarily adopted by users who anticipate self-control challenges and seek technological support to manage them. This autonomous and transparent nature is a defining characteristic of BCSS [5] and aligns closely with Duckworth and colleagues' notion of self-deployed strategies, distinguishing BCSS from paternalistic nudging approaches.

Importantly, existing BCSS research already contains examples of systems corresponding to the main mechanistic categories identified in self-control theory. Prior work in the Persuasive Systems community has already discussed individual cognitive strategies such as goal setting [24] and situational strategies that allow users to restructure their environments to avoid temptations [e.g., 25]. However, these systems are rarely discussed explicitly as self-control interventions, limiting cross-domain integration and theory-driven comparison. Furthermore, digital training-based interventions have not yet been discussed extensively in the BCSS community.

3. Methods

3.1. Search Strategy and Inclusion Criteria

For the systematic search, the updated PRISMA guidelines [26] were followed. Four databases were searched: AISeLibrary, ACM Library, APA PsycInfo, and Business Source Premier, covering IS, Human-Computer Interaction (HCI), Psychology/Neuroscience, and Business/Economics literature, respectively. Search terms targeted (1) interventions (nudg* OR boost* OR (behave* AND intervention*) OR (behav* AND change)) that were (2) applied digitally (digit* OR "information system*" OR technolog* OR app* OR "virtual reality" OR smartphone* OR online*) and a broad range of terms related to (3) self-control (self-control OR self-regulat* OR self-nudg* OR "present bias" OR "future orient*" OR "goal orient*" OR "delay of gratification" OR "delay discounting" OR impuls* OR "intertemporal choice*" OR "temporal disctanc*" OR willpower OR conscientious* OR "cognitive effort" OR "cognitive control" OR "executive function*" OR "executive control"). The three keyword groups were combined using "AND" and applied to titles, abstracts, and keywords in ACM, PsycInfo, and Business Source Premier, as well as to "all fields" in AISeLibrary. As detailed in Figure 1, after limiting results to the past 10 years, peer-reviewed, and English-language, 3,705 records were retrieved in total. After removing duplicates, titles and abstracts of 3,510 studies underwent a manual screening followed by full-text screening of 381 references. All searches were conducted in September 2024.

Eligibility criteria included studies that (1) described fully automated digital behavioral interventions, (2) provided formal quantitative tests of their effectiveness in human participants using (quasi-)experimental designs, and (3) focused on real-world choice behaviors (B-Change; see Oinas-Kukkonen, 2010). Furthermore, (4) only studies testing interventions that were designed for self-application to increase self-control and self-governed adherence towards long-term goals were included. For example, a study testing the effectiveness of inducing a waiting period before checkout in an online store using a browser extension tool [e.g., 27] would be included while a study using the same mechanism but embedded in an online webstore beyond the users' control would not.

Furthermore, studies involving clinical populations (i.e., post-stroke rehabilitation or DSM 5 criteria) or children under 16 years old were excluded, as these populations often rely on external guidance rather than autonomous self-control efforts. After title and abstract screening, 3,129 studies were excluded.

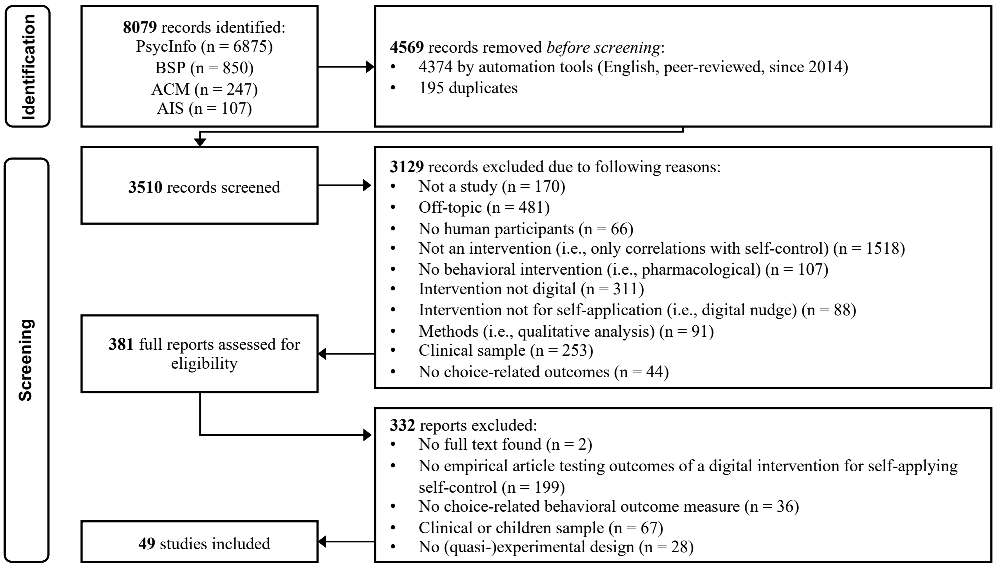

Figure 1: Search and Screening Process following PRISMA guidelines [26].

Full-text screening of the remaining 381 references led to the exclusion of an additional 332 studies for reasons such as describing non-digital interventions, non-self-applied tools (e.g., paternalistic nudging), or lack of real-world behavioral outcomes. The final dataset included 49 studies for analysis. A detailed summary of this screening process is shown in Figure 1.

3.2. Synthesis and Analysis

The analysis followed a qualitative systematic literature review approach (see [11]) to synthesize findings from diverse literature with varying sample sizes and measurement techniques. Each eligible reference was screened to identify distinct digital self-control interventions tested against either a pre-intervention baseline or control group, allowing for assessment of their isolated effectiveness. These interventions were categorized according to intervention type, delivery medium, target behavior, and effectiveness.

Intervention types were grouped into three pre-defined categories: cognitive, situational, or training. Cognitive interventions, according to Duckworth and colleagues, aim to "change the way [people] think, making long-term goals more appealing or short-term temptations less so" 7, p. 108. These include tools for goal setting, distal feedback, planning, mindfulness practices, or making future consequences more relatable (sub-categories derived inductively). Situational interventions assist in directly modifying the environment where choices are made, such as blocking access to temptations or offering real-time feedback [7, 23]. Duckworth et al.'s binary classification was extended by a third category: training interventions. These focus on exercises to build self-control capacity or entrain automatic response tendencies [20, 21]. Although not without conceptual overlaps, training interventions were dissociated from cognitive interventions as they provide direct exercises to build self-control capacity or reduce intrinsic impulsive approach tendencies towards goal-incongruent temptations [20, 21] while cognitive interventions rather focus on inducing explicit cognitions or changing transient mental states.

Categories for delivery medium and target outcome behavior were developed iteratively during screening. Effectiveness was categorized based on statistically significant results ($p < .05$). Interventions were deemed effective if they produced consistent and statistically significant changes in at least one relevant choice-related outcome compared to baseline or a control group. They were classified as ineffective if no significant effect was found. Mixed results were identified if either (1) effects occurred against baseline, but not a control condition, (2) effects were inconsistent over time points, (3) effects only applied to subpopulations (e.g., specific age groups), or (4) effects were not replicated in follow-up studies within the same article.

Table 1
Frequencies of tested tools across categories by intervention domain.

Interventions	Training	Situational	Cognitive	Total
Total	10	24	38	72
Intervention Delivery Medium				
Web-based	5 (50%)	1 (4%)	22 (58%)	28 (39%)
Smartphone App	–	11 (46%)	14 (37%)	25 (35%)
Browser Extension	–	10 (42%)	–	10 (14%)
Desktop-based (local)	5 (50%)	–	1 (2.5%)	6 (8%)
Smart Home Tools	–	2 (8%)	–	2 (3%)
Virtual Reality	–	–	1 (2.5%)	1 (1%)
Target Behavior Domain				
Digital (i.e., screen time reduction, online purchases)	–	17 (71%)	2 (5%)	19 (26%)
Non-digital (i.e., diet, physical activity, eco-driving)	10 (100%)	7 (29%)	36 (95%)	53 (74%)
Effectiveness				
Yes	3 (30%)	20 (83%)	20 (53%)	43 (60%)
Mixed	4 (40%)	1 (4%)	4 (10%)	9 (12%)
No	3 (30%)	3 (13%)	14 (37%)	20 (28%)

Note: Percentages describe a cell's frequency relative to the respective column total (i.e., "Cognitive").

4. Findings from the Literature Review

In the 49 eligible studies, 72 distinct BCSS features or feature combinations were tested for improving long-term goal pursuit. About half of all eligible studies were published in digital-focused fields (e.g., Digital Health, HCI, IS). The rest appeared in psychology or outcome-specific outlets such as diet or education. As shown in Table 1, most interventions were web- or app-based, followed by browser extensions and desktop prototypes tested locally in laboratory settings. Two interventions involved smart home interventions, and one used virtual reality. Only 26% of the 72 interventions targeted behaviors in digital domains, such as reducing digital media use (16%), online purchases (7%), or improving cyber security (3%). The remaining 74% of interventions focused on non-digital behaviors, mainly dieting or physical activity (49%) and other health-related actions (7%). Some interventions aimed to improve self-control in academic performance (11%) or reduce risky driving (1%), or allowed users to define their own goals (6%). 60% of all interventions successfully affected behavior, 28% had no effect, and 12% showed mixed results.

Categorizing the 72 interventions regarding their approach to support self-control revealed that most were cognitive interventions (53%), mainly delivered via web interfaces and smartphone apps and primarily targeting non-digital outcome domains (i.e., diet or physical activity), followed by situational interventions (33%) often implemented in smartphone apps and browser extensions most often focusing on changing behaviors in digital domains (i.e., social media consumption), and training interventions either tested via web interfaces or on desktops locally in the laboratory that exclusively focused on improving dietary or physical activity-related outcomes in our sample of studies. Furthermore, several intervention subtypes were inductively identified as listed in Table 2 among the three major intervention categories. In the following, each intervention category will be evaluated separately to reveal the main strengths and weaknesses and the necessary trade-offs when applying them.

4.1. Training Self-Control

Seven studies examined ten distinct digital interventions designed to directly enhance self-control capacity or modify intrinsic response tendencies through neurocognitive tasks. All of them focused on either diet-related or physical activity outcomes. Two aimed to increase domain-general self-control capacity by repeatedly applying working memory or inhibitory control training [42, 28]. For example, in Dassen et al. [28], the intervention group demonstrated improved working memory capacity compared

Table 2
Inductive clusters of intervention (sub-)types and their effectiveness

Interventions	Examples	Effective
Self-Control Training Interventions		**3/10 (30%)**
Domain-General	25 sessions of working memory training [28]	0/2 (0%)
Domain-Specific	Go-/no-go task with stop cues paired with unhealthy foods [29]	3/5 (60%)
Automatic Response Tendencies	Approach-Avoidance Training approaching healthy and avoiding unhealthy foods [30]	0/3 (0%)
Cognitive Interventions		**20/38 (53%)**
GS/FB/MC without IIs	Smartphone app for physical activity goal setting and progress tracking [31]	3/8 (38%)
GS/FB/MC with IIs	Weight tracking app with daily planning, reflection, and evaluation prompts [32]	14/21 (67%)
Mindfulness	Audio-guided mindful breathing and presence focus [33]	2/4 (50%)
Making the future relatable	Audio guides for episodic future thinking [34] or connecting with a virtual future self [35]	1/5 (20%)
Situational Interventions		**20/24 (83%)**
Block / Removal	Waiting period before online shopping checkout [27] or removing tempting news feeds from Facebook [36]	4/6 (67%)
Goal advancement	AI-assisted diet goal reminders during eating [37] or prompts with dismiss options during video watching [38]	7/7 (100%)
Self-Tracking	Real-time basket feedback in grocery shopping [39] or eco-driving feedback [40]	6/8 (75%)
Rewards/Punish	Prompts highlighting expected monetary rewards/losses for meeting or failing screen time goals [41]	1/1 (100%)
Combinations of the above	The "OneSec" app induces waiting periods, provides goal reminders, and offers dismiss options when opening a target app [38]	2/2 (100%)

Note: GS – Goal Setting, FB – Feedback, MC – Mental Contrasting, II – Implementation Intentions

to a food education control group. However, these gains did not translate into broader improvements in executive functions, nor did they lead to reductions in food intake or BMI.

In contrast, five interventions targeted domain-specific self-control, aiming to train individuals to resist the temptation of high-calorie foods specifically. For instance, Veling et al. [29] implemented four 30-minute sessions of a web-based go/no-go task over four weeks. Participants had to inhibit habitual responses when presented with images of unhealthy foods. The study found that domain-specific inhibitory control training resulted in statistically significant reductions in body weight, outperforming domain-general inhibitory control training. However, such effects may be short-lived and context dependent. Allom and Mullan [42] reported that while BMI decreased immediately after the training phase, these effects did not persist after seven days without intervention. Additionally, a second experiment failed to replicate the initial findings.

Three other studies focused on altering implicit preferences for healthier choices using approach-avoidance training. In these tasks, participants were shown images of healthy and unhealthy foods. They were instructed to simulate approach responses for healthy foods and avoidance responses for unhealthy ones [e.g., 30]. However, none of these interventions affected dietary behavior.

4.2. Cognitive Interventions

Most of the interventions identified were categorized as cognitive interventions that can be further subdivided into three main subtypes, as shown in Table 2.

First, many digital intervention tools aim to support long-term goal pursuit by directly acting on these goals. These tools encourage users to articulate their goals (goal setting), develop specific action plans to achieve them (implementation intentions), anticipate potential obstacles (mental contrasting), and provide explicit feedback or promote self-tracking of progress (feedback). In simpler versions, these tools offer a digital platform for self-tracking or prompt users to regularly update their goal-progress logs [e.g., 31]. Others provide automated feedback at pre-defined intervals [e.g., 43]. As summarized in Table 2, these interventions were generally ineffective when used alone across various outcome domains. However, their effectiveness increased when combined with implementation intentions—concrete action plans often framed as if-then statements, such as "If I open the fridge, I will think of dieting" [29, p. 104]. When paired with implementation intentions, such interventions have been largely effective in improving dietary choices [e.g., 32], promoting physical activity [e.g., 44], and reducing procrastination during learning [45]. Importantly, findings from a large-scale study suggest that a single planning session is insufficient to sustain adherence to study plans [46]. This indicates that repeated planning may be necessary for lasting success.

Second, the evidence for digital mindfulness interventions was mixed. For instance, Mitchell et al. [33] reported the positive effects of a mindful breathing exercise delivered through digital audio guides on physical exercise duration. However, Friederichs et al. [47] found no evidence that an affective state-shift exercise improved emotion regulation capacity, leading to more self-set goals being acted upon.

Third, a set of interventions focused on making the future consequences of current behaviors more relatable. Some utilized digital audio guides to help individuals simulate self-related future events—a technique known as Episodic Future Thinking (EFT)—to reduce present bias in decision-making. While EFT has shown reliable effects on tasks assessing future-oriented decision-making in laboratory settings and holds some promise for increasing exercise behavior [e.g., 33], it has occasionally failed to generalize to real-world outcomes [34]. Other related interventions used digital technology to visualize users' future selves and enable interactions [e.g., 35]. However, these interventions have shown only limited effects.

4.3. Situational Interventions

24 tested interventions from 13 studies were identified as situational, primarily published in digital fields, with 9 articles published in the HCI literature and 2 from the IS field. Accordingly, most interventions were designed to assist self-control in digital outcome domains, such as controlling digital media consumption (10 interventions), reducing impulsive buying behavior online (5 interventions), or helping adhere to cyber security protocols (2 interventions). The remaining nine interventions targeted non-digital outcome domains, such as dietary and other health-related behaviors and risky driving.

As shown in Table 2, four sub-categories of situational interventions were identified paralleling those reported by Lyngs et al. [23] from the digital device use domain: Block/removal, goal advancement, self-tracking, reward/punish, or combinations thereof. Apart from their frequent applications in managing digital device use (i.e., screen time), some block/removal tools deliberately induced waiting periods before allowing users to proceed to checkout to reduce impulsive buying online [27]. Furthermore, one goal advancement tool provided individually tailored goal reminders at specific time points, such as during eating, by integrating AI [37] and Degirmenci et al. [40] allowed for self-tracking of behavior in real-time by showing visualized feedback on the current driving style to improve eco-friendly driving. The one study identified in the rewards/punish category provided monetary micro-incentives to motivate keeping up with self-set screen time limits by sending reminders on the money users were about to win or lose if keeping up with this goal or not shortly before the limit was reached [41]. Across sub-categories, situational interventions were highly effective.

5. Discussion

This systematic literature review analyzes 49 studies that quantitatively assessed the effectiveness of 72 dissociable digital BCSS interventions aiming to promote long-term-oriented behaviors (self-control). Digitally delivered training, cognitive, and situational interventions were identified based on previous taxonomies of behavioral self-control interventions from non-digital contexts [7] and interventions for reducing digital device use [23]. These were applied across various outcome domains, from curbing impulse buying online to promoting healthy diets and physical activity and reducing procrastination during learning and were evaluated with a varying degree of quality ranging from controlled laboratory experiments to large-scale randomized controlled trials in naturalistic settings.

Although the analysis provided here does not take effect estimates or methodological quality assessments into account, the qualitative synthesis offers valuable insights into emerging themes, design recommendations, and areas for future research that are formulated in six propositions outlined below. Propositions 1 through 3 hold practical design implications, while Propositions 4 through 6 reflect methodological considerations for future research.

5.1. Propositions for BCSS Design and Practice

Empirical support for the effectiveness of situational strategies First, while most identified studies employed cognitive interventions such as goal setting or implementation intentions, the most promising were situational strategies—83% showed significant effects compared to 53% for cognitive and 30% for training interventions. Although this finding should be considered preliminary and descriptive and does not account for the studies' methodological quality and publication bias, it empirically backs claims made by earlier non-systematic reviews on self-control in non-digital contexts, noting that "situational self-control strategies may be as effective as they are underappreciated" [12, p. 50].

For designers of BCSS, this points towards an important insight: Rather than focusing on features that need to repeatedly persuade individuals into acting in line with their goals, they might focus on providing the means to restructure the environment - so that desired behaviors become easier. In BCSS terminology, this limits the necessity to repeatedly target the direct route of persuasion (only once when planning and installing the adaptations of the choice environment) but externalizes self-control to the environment. For this, designers can build on the large body of IS research on digital nudges. By transforming these nudges into self-nudges [i.e., see 48] — where participants are informed about the benefits of a nudge and can choose to apply it to themselves for their own benefit — such interventions have already demonstrated effectiveness in IS [e.g., 49].

However, one caveat regarding situational interventions should be noted. Like a prosthesis, these tools likely only work while consistently applied; once removed, behavior may revert to pre-intervention levels [see 50]. Future research should investigate how BCSS focusing on situational interventions can also foster additional learning and habit-forming effects that enable long-term benefits even when the system aid is removed, avoiding overreliance that might hinder individuals from developing cognitive self-regulation skills.

P1: Digital BCSS that implement situational strategies may be particularly effective in promoting behavior change across various domains (e.g., diet, physical activity, digital device use). However, their long-term effectiveness may depend on the consistent application of these tools and the extent to which they foster autonomous self-regulation skills without creating over-reliance.

Refining cognitive strategies with action planning While the effectiveness of cognitive strategies appears mixed in this study sample, one particularly promising subgroup stands out: interventions incorporating implementation intentions. Simple approaches such as distal feedback, goal setting, and mental contrasting alone do not consistently improve goal pursuit. Furthermore, no consistent evidence could be found yet supporting mindfulness- or EFT-based interventions.

However, when combined with concrete action plans, cognitive interventions become effective across many studies [e.g., 32]. The findings reported here thus confirm suggestions made by earlier non-systematic reviews on digital behavior change tools [e.g., 8] and suggest that assisting individuals in progressing from vague goal representations to forming actionable and automatable plans is crucial for goal attainment. This also empirically backs the centrality of the first PSD design principle of "Reduction" - reducing complex behaviors into simpler tasks. Thus, the findings propose that BCSS providing cognitive interventions should focus on action planning. This can be done by explicitly delivering tailored plans, such as using adaptive, personalized recommendations based on current performance [45] or prompting users to develop action plans themselves [32].

Moreover, it becomes clear that a single application of any cognitive intervention—regardless of its specific nature—tends to not be very effective in the long run but that achieving sustained success in long-term goals, such as studying for exams or adhering to a healthy lifestyle, requires repeated intervention over time [46]. This also underscores the central claim made by the PSD model that "persuasion may be considered as a process rather than as a single act" [4, p. 3].

P2: BCSS based on cognitive self-control strategies are most effective when they incorporate concrete action plans through personalized recommendations or user-generated plans. Repeated engagement over time is necessary for sustained success.

Rethinking self-control training: Domain-specificity may be key The evidence for digitally delivered self-control training interventions seems relatively sparse and is particularly limited to small-scale laboratory studies. Overall, only 3 out of 10 identified intervention studies reported a statistically significant effect on relevant outcome measures. Domain-general training interventions such as working memory or domain-general inhibitory control training have often been proposed to be a promising tool for building general self-control capacity and long-term goal pursuit [51] and have occasionally shown promise in non-digital application settings [e.g., 22]. However, the studies included here do not support their effectiveness when delivered through digital tools. In general, the strength model account and the metaphor of self-control as a trainable muscle have been criticized, and a meta-analysis formulated considerable doubts on the generalizability of self-control training beyond domain- and task-specific practice effects [52]. In line with these arguments, all training interventions that could show a significant effect here targeted domain-specific self-control, i.e., training inhibitory control specifically for resisting unhealthy food options [e.g., 29].

Hence, despite the widely popular notion of self-control as a general, trainable resource, designers of such features should appreciate the possibility that there might not be a generalizable self-control resource that can be trained across domains. Instead, developing training interventions tailored to specific behavioral target outcomes, such as increasing inhibitory control of unhealthy foods in a particular context, may be more effective. Emerging technologies like virtual reality (VR) could further enhance such training by simulating real-world contexts where target behaviors occur. However, to my knowledge, such self-control training interventions have not yet been systematically tested (i.e., RCTs) in outcome domains beyond the dietary context. Hence, their applicability to other areas—such as reducing digital device use—remains to be empirically tested. The BCSS field is well-positioned to explore this avenue in future research. This results in the third proposition:

P3: Instead of focusing on increasing a domain-general self-control capacity, digital self-control training interventions should target specific behavioral outcomes.

5.2. Propositions for Future Research

Unequal Distribution of Intervention Strategies across Outcome Domains Overall, the sample of studies reviewed here reveals an unequal distribution of studies testing the three intervention categories (training, cognitive, situational) across different outcome domains.

First, while situational interventions are strongly researched in the context of inherently digital outcome domains, such as reducing digital device use [e.g., 38], or reducing online impulse buying behaviors [e.g., 27], only a small subset of interventions targeting non-digital behaviors used situational approaches (7 out of 53). This is not surprising as designing situational self-control tools is relatively straightforward in digital outcome domains (i.e., placing digitally delivered reminders when opening Instagram) but inherently more challenging in non-digital outcome domains, such as improving diet or physical activity. Nevertheless, some studies identified here offer valuable ideas for achieving this. For example, Lee et al. [53] provided participants with smart home tools such as smart speakers and a range of sensors, along with instructions on how to effectively modify at-home choice architectures. Given their high potential, such additional effort regarding technical equipment and study design may well pay off and future studies should set out to test such innovative situational approaches beyond digital outcome domains.

Second, and inversely to the previous point, studies of digital outcome domains have a bias towards such situational strategies - only 2 out of 19 studies tested cognitive and none applied training strategies. Despite the success of situational strategies in digital domains, they might additionally benefit from cognitive or training strategies, i.e., to offset the above-mentioned reversals to baseline after removal of the intervention tool. These considerations drive the fourth proposition:

P4: Behavior change designers and researchers focusing on non-digital outcome behaviors (i.e., diet, physical activity) should more strongly explore the application of situational strategies with digital tools (i.e., self-nudges using smart home tools). In contrast, interventions targeting digital outcome behaviors (i.e., reducing digital device use) might additionally benefit from cognitive and training strategies for sustainable intervention success in case the intervention is removed.

Flexible research designs in testing multi-component interventions Many studies identified tested multiple intervention components simultaneously, making it challenging to disentangle the specific contributions of each part. While this is common and desired in applied research, it remains crucial to isolate the individual components that are most effective. Understanding which aspects of an intervention drive its success could lead to more targeted and efficient designs. Future research could employ more flexible study designs, such as micro-randomized controlled trials (MRTs) [e.g., 54], to address this challenge. MRTs offer a convenient way to evaluate multiple intervention features without creating additional subject groups for each variation of the intervention [55]. This approach could help optimize multi-component interventions by systematically testing and refining individual elements. These perspectives lead to the following proposition:

P5: Future studies should adopt flexible research designs like micro-randomized controlled trials (MRTs) to improve the understanding and effectiveness of multi-component interventions.

Studies usually do not directly estimate their interventions' real-world adoption Although all studies reviewed here evaluated tools intended for self-application (i.e., self-tracking apps or browser extensions), not all research designs aligned with this principle. For most cognitive interventions, transparency was inherent (e.g., goal setting, implementation intentions), but situational interventions often lacked this feature. For example, Han et al. [27] tested a range of interventions designed to reduce impulse buying online. Despite implementing them in a browser extension that users would need to actively install themselves when put into practice, participants in their study context were randomly assigned to the intervention groups without disclosure of the interventions' nature or purpose and without an explicit opt-in choice. This raises doubts about whether the results truly allow for inferences on their real-world adoption and effectiveness. A similar pattern was observed in training interventions, where their concrete purpose and mechanisms were mainly not disclosed, and voluntary uptake was not assessed.

This reflects a common trade-off: while random assignment and limited disclosure prioritize internal validity and causal inference, they may not predict effectiveness when users must opt in voluntarily. Some studies offer promising strategies. For example, Michels et al. [49] allowed participants to opt into a self-nudge in online groceries after being informed about its purpose - more closely mirroring real-world conditions.

Beyond the study sample reviewed here, in a recent preprint Stock et al. [56] proposed an even more refined design combining an initial randomization with voluntary opt-in before a second randomization determined actual exposure. Integrating such estimates of voluntary adoption early on may help alleviate concerns about the predictiveness of experimental findings for real-world effectiveness.

P6: Future research should systematically evaluate the adoption, sustained use, and effectiveness of self-control interventions by integrating designs that combine randomization with voluntary uptake and transparent disclosure, thereby more accurately reflecting real-world conditions.

5.3. Mapping self-control interventions to PSD design principles

While several established PSD design principles [4] - particularly from Primary Task Support (e.g., reduction, self-monitoring, tunneling) and Dialogue Support (e.g., reminders, rewards) categories - are reflected in situational and cognitive self-control interventions, there are two notable gaps worth highlighting for the BCSS community.

First, training interventions map narrowly onto the PSD framework, primarily corresponding to rehearsal. However, PSD conceptualizes rehearsal as behavioral practice rather than neurocognitive capacity building, suggesting training-based approaches fall partially outside the model's scope—an opportunity for BCSS research to integrate cognitive training insights. Second, two PSD categories remain largely unaddressed in the self-control intervention literature reviewed here: System Credibility Support and Social Support. Here, self-control research could benefit from adopting guidance offered by the PSD model such as regarding social support mechanisms (i.e., social comparison or normative influence). For example, BCSS could advise users to actively engineer their social environment, leveraging social norms as a form of self-nudge to support their goals (e.g., joining accountability groups, publicly committing to behavior change, or surrounding oneself with peers who model desired behaviors).

5.4. Limitations

Some limitations should be acknowledged, which affect the generalizability of the findings reported here and point to important directions for future research. First, despite broad search terms, relevant studies using alternative terminology may have been missed. The findings should be interpreted as an idea-sparking snapshot rather than a comprehensive overview. Second, studies focusing on interventions aimed at children and clinical populations were excluded, limiting the scope of the findings to healthy adult samples. It is well-established that self-control can vary substantially across different age groups and between healthy individuals and those with clinical conditions such as attention-deficit hyperactivity disorder (ADHD), obsessive-compulsive disorder (OCD), or substance use disorders [13]. For instance, while self-control aids may be beneficial for individuals with substance use disorders, for others—such as those with OCD—excessive exertion of self-control can be part of their pathology and might thus be counterproductive [57]. This suggests that increasing self-control may not always be desirable or appropriate and should be carefully tailored to the needs of specific populations. Future research should investigate how digital self-control interventions need to be adapted for different age groups and clinical conditions. Third, the categorization into cognitive, situational, and training tools has inherent limitations. For example, feedback features were categorized as cognitive interventions when applied more distally from actual decision-making moments. In contrast, similar interventions were categorized as situational when offering information directly during a choice situation (e.g., real-time feedback on driving behavior [40]). However, this distinction is not always clear-cut. In some cases, the categorization may depend more on how users interact with the tool over time rather than on the tool's design alone. Fourth, all screening and data extraction was conducted by a single reviewer, which may introduce selection bias and limits the reproducibility of the screening decisions. Lastly, the classification of effectiveness relied solely on statistical significance ($p < .05$) without formal assessment of effect sizes, study quality (i.e., small in-lab studies vs. large-scale field studies), risk of bias, or publication bias [26]. Consequently, all included studies were treated with equal evidential weight regardless of their methodological rigor. The reported effectiveness rates hence need to be interpreted as descriptive summaries rather than effect estimates and the following propositions (propositions 1-3) should be verified with more rigorous meta-analytic approaches in future research.

6. Conclusion

This review synthesized evidence from 49 studies testing 72 digital self-control tools, developing six propositions for practice and research. Propositions 1 to 3 are particularly relevant for practitioners and BCSS designers. They emphasize the promise of situational strategies (P1) and the strong evidence for the effectiveness of implementation intentions (P2), and suggest the importance of aligning training and target behavior contexts when designing self-control trainings (P3). These findings underscore arguments from previous narrative theoretical work [12, 8] with more systematic evidence. Propositions 4 to 6 especially hold suggestions for future research directions. They call for applying situational strategies beyond digital outcome domains (P4), employing flexible, innovative research designs like micro-randomized controlled trials to disentangle multi-component interventions (P5), and enriching gold standard RCT designs with features allowing a first assessment of whether self-applied digital interventions might actually be adopted and used in real-world settings (P6). These points highlight important methodological opportunities for the BCSS field to advance the development and evaluation of self-deployed BCSS. Lastly, the findings reported here demonstrate several overlaps between interventions built on self-control theories directly and those designed from BCSS frameworks. However, they also show some gaps on both sides: an under-representation of social support tools in self-control research and an opportunity for integrating ideas around self-control training interventions in BCSS research. Overall, this review provides BCSS researchers and practitioners with a comprehensive and structured overview of current digital BCSS from a self-control theory perspective, facilitating the transfer of effective design ideas across different behavioral domains.

Declaration on Generative AI

During the preparation of this work, the author used Claude AI for citation formatting, making suggestions for shortening of content, and improving language and grammar. The author reviewed and edited all generated content and takes full responsibility for the publication's content.

References

[1] R. H. Thaler, C. R. Sunstein, Nudge: Improving Decisions about Health, Wealth, and Happiness, Nudge: Improving Decisions about Health, Wealth, and Happiness, Yale University Press, New Haven, CT, US, 2008.

[2] C. Schneider, M. Weinmann, J. vom Brocke, Digital nudging: Guiding online user choices through interface design, Communications of the ACM 61 (2018) 67–73. doi:10.1145/3213765.

[3] T.-B. Lembcke, N. Engelbrecht, A. B. Brendel, L. Kolbe, To nudge or not to nudge: Ethical considerations of digital nudging based on its behavioral economics roots., ECIS 2019 Proceedings (2019).

[4] H. Oinas-Kukkonen, M. Harjumaa, Persuasive Systems Design: Key Issues, Process Model, and System Features, Communications of the Association for Information Systems 24 (2009). doi:10.17705/1CAIS.02428.

[5] H. Oinas-Kukkonen, Behavior Change Support Systems: A Research Model and Agenda, in: T. Ploug, P. Hasle, H. Oinas-Kukkonen (Eds.), Persuasive Technology, Springer, Berlin, Heidelberg, 2010, pp. 4–14. doi:10.1007/978-3-642-13226-1_3.

[6] A. M. Roffarello, L. De Russis, Achieving Digital Wellbeing Through Digital Self-control Tools: A Systematic Review and Meta-analysis, ACM Trans. Comput.-Hum. Interact. 30 (2023) 53:1–53:66. doi:10.1145/3571810.

[7] A. L. Duckworth, K. L. Milkman, D. Laibson, Beyond Willpower: Strategies for Reducing Failures of Self-Control, Psychological Science in the Public Interest 19 (2018) 102–129. doi:10.1177/1529100618821893.

[8] C. Pinder, J. Vermeulen, B. R. Cowan, R. Beale, Digital Behaviour Change Interventions to Break and Form Habits, ACM Trans. Comput.-Hum. Interact. 25 (2018) 15:1–15:66. doi:10.1145/3196830.

[9] M. S. Haque, S. Iyengar, P. Karppinen, L. van Gemert-Pijnen, H. Oinas-Kukkonen, What do we know about behavior change support systems after a decade of annual meetings?, CEUR Workshop Proceedings (2023).

[10] H. Oinas-Kukkonen, S. Nabwire, E. Vlahu-Gjorgievska, S. Iyengar, 12 years of research into behavior change support systems, in: BCSS 2024: The 12th International Workshop on Behavior Change Support Systems, April 10, 2024, Wollongong, Australia, 2024.

[11] G. Paré, M.-C. Trudel, M. Jaana, S. Kitsiou, Synthesizing information systems knowledge: A typology of literature reviews, Information & Management 52 (2015) 183–199. doi:10.1016/j.im.2014.08.008.

[12] A. L. Duckworth, T. S. Gendler, J. J. Gross, Situational Strategies for Self-Control, Perspectives on Psychological Science 11 (2016) 35–55. doi:10.1177/1745691615623247.

[13] J. T. Nigg, Annual Research Review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology, Journal of Child Psychology and Psychiatry 58 (2017) 361–383. doi:10.1111/jcpp.12675.

[14] R. F. Baumeister, E. Bratslavsky, M. Muraven, D. M. Tice, Ego depletion: Is the active self a limited resource?, Journal of personality and social psychology 74 (1998) 1252–1265. doi:10.1037/0022-3514.74.5.1252.

[15] D. Kahneman, A perspective on judgment and choice: Mapping bounded rationality, American Psychologist 58 (2003) 697–720. doi:10.1037/0003-066X.58.9.697.

[16] W. Hofmann, M. Friese, F. Strack, Impulse and Self-Control From a Dual-Systems Perspective, Perspectives on Psychological Science 4 (2009) 162–176. doi:10.1111/j.1745-6924.2009.01116.x.

[17] A. Shenhav, S. Musslick, F. Lieder, W. Kool, T. L. Griffiths, J. D. Cohen, M. M. Botvinick, Toward a Rational and Mechanistic Account of Mental Effort, Annual Review of Neuroscience 40 (2017) 99–124. doi:10.1146/annurev-neuro-072116-031526.

[18] T. E. Moffitt, L. Arseneault, D. Belsky, N. Dickson, R. J. Hancox, H. Harrington, R. Houts, R. Poulton, B. W. Roberts, S. Ross, M. R. Sears, W. M. Thomson, A. Caspi, A gradient of childhood self-control predicts health, wealth, and public safety, Proceedings of the National Academy of Sciences 108 (2011) 2693–2698. doi:10.1073/pnas.1010076108.

[19] J. M. Rung, G. J. Madden, Experimental reductions of delay discounting and impulsive choice: A systematic review and meta-analysis, Journal of Experimental Psychology: General 147 (2018) 1349–1381. doi:10.1037/xge0000462.

[20] E. T. Berkman, A. M. Graham, P. A. Fisher, Training Self-Control: A Domain-General Translational Neuroscience Approach, Child Development Perspectives 6 (2012) 374–384. doi:10.1111/j.1750-8606.2012.00248.x.

[21] T. Smith, K. Panfil, C. Bailey, K. Kirkpatrick, Cognitive and Behavioral Training Interventions to Promote Self-Control, Journal of Experimental Psychology: Animal Learning and Cognition 45 (2019) 259–279. doi:10.1037/xan0000208.

[22] F. Kehr, M. Hassenzahl, M. Laschke, S. Diefenbach, Transformational products: Development of ubiquitous interaction devices to enhance self-control, in: Proceedings of the Designing Interactive Systems Conference, ACM, 2012, pp. 696–705. doi:10.1145/2317956.2318064.

[23] U. Lyngs, K. Lukoff, P. Slovak, R. Binns, A. Slack, M. Inzlicht, M. Van Kleek, N. Shadbolt, Self-Control in Cyberspace: Applying Dual Systems Theory to a Review of Digital Self-Control Tools, in: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, CHI '19, Association for Computing Machinery, New York, NY, USA, 2019, pp. 1–18. doi:10.1145/3290605.3300361.

[24] S. Consolvo, P. Klasnja, D. W. McDonald, J. A. Landay, Goal-setting considerations for persuasive technologies that encourage physical activity, in: Proceedings of the 4th International Conference on Persuasive Technology, ACM, 2009, pp. 1–8. doi:10.1145/1541948.1541960.

[25] L. Manzke, Designing a Digital Behavior Change Intervention for Online Grocery Stores: A Randomized Controlled Trial, in: BCSS 2025: The 13th International Workshop on Behavior Change Support Systems, 2025.

[26] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, et al., The PRISMA 2020 statement: An updated guideline for reporting systematic reviews, International Journal of Surgery

88 (2021) 105906. doi:10.1016/j.ijsu.2021.105906.

[27] Y. Han, H. Kim, H. Chu, J. Kim, H. Lee, S. Choe, D. Jung, D. Chung, B. C. Kwon, S. Ko, Wait, let's think about your purchase again: A study on interventions for supporting self-controlled online purchases, in: Proceedings of the Web Conference 2021, Www '21, Association for Computing Machinery, New York, NY, USA, 2021, pp. 2476–2487. doi:10.1145/3442381.3450021.

[28] F. C. M. Dassen, K. Houben, G. J. P. Van Breukelen, A. Jansen, Gamified working memory training in overweight individuals reduces food intake but not body weight, Appetite 124 (2018) 89–98. doi:10.1016/j.appet.2017.05.009.

[29] H. Veling, G. M. van Koningsbruggen, H. Aarts, W. Stroebe, Targeting impulsive processes of eating behavior via the internet. Effects on body weight, Appetite 78 (2014) 102–109. doi:10.1016/j.appet.2014.03.014.

[30] H. Veling, Z. Chen, M. C. Tombrock, I. A. M. Verpaalen, L. I. Schmitz, A. Dijksterhuis, R. W. Holland, Training impulsive choices for healthy and sustainable food, Journal of Experimental Psychology: Applied 23 (2017) 204–215. doi:10.1037/xap0000112.

[31] C. Berli, U. Scholz, Long-term and transfer effects of an action control intervention in overweight couples: A randomized controlled trial using text messages, Frontiers in Psychology 12 (2021). doi:10.3389/fpsyg.2021.754488.

[32] K. Frie, J. Hartmann-Boyce, S. A. Jebb, P. Aveyard, Effectiveness of a self-regulation intervention for weight loss: A randomized controlled trial, British Journal of Health Psychology 25 (2020) 652–676. doi:10.1111/bjhp.12436.

[33] A. D. Mitchell, L. E. Martin, A. S. Baldwin, S. M. Levens, Mindfulness-informed guided imagery to target physical activity: A mixed method feasibility and acceptability pilot study, Frontiers in Psychology 12 (2021). doi:10.3389/fpsyg.2021.742989.

[34] L. H. Epstein, R. A. Paluch, M. J. Biondolillo, J. S. Stein, T. Quattrin, L. D. Mastrandrea, K. Gatchalian, M. H. Greenawald, W. K. Bickel, Effects of 6-month episodic future thinking training on delay discounting, weight loss and HbA1c changes in individuals with prediabetes, Journal of Behavioral Medicine 45 (2022) 227–239. doi:10.1007/s10865-021-00278-y.

[35] A. Mönninghoff, K. Fuchs, J. Wu, J. Albert, S. Mayer, The Effect of a Future-Self Avatar Mobile Health Intervention (FutureMe) on Physical Activity and Food Purchases: Randomized Controlled Trial, Journal of Medical Internet Research 24 (2022) e32487. doi:10.2196/32487.

[36] U. Lyngs, K. Lukoff, P. Slovak, W. Seymour, H. Webb, M. Jirotka, J. Zhao, M. Van Kleek, N. Shadbolt, 'I just want to hack myself to not get distracted': Evaluating design interventions for self-control on facebook, in: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, Chi '20, Association for Computing Machinery, New York, NY, USA, 2020, pp. 1–15. doi:10.1145/3313831.3376672.

[37] H. S. J. Chew, N. W. S. Chew, S. S. E. Loong, S. L. Lim, W. S. W. Tam, Y. H. Chin, A. M. Chao, G. K. Dimitriadis, Y. Gao, J. B. Y. So, A. Shabbir, K. Y. Ngiam, Effectiveness of an artificial intelligence-assisted app for improving eating behaviors: Mixed methods evaluation, Journal of Medical Internet Research 26 (2024). doi:10.2196/46036.

[38] D. J. Grüning, F. Riedel, P. Lorenz-Spreen, Directing smartphone use through the self-nudge app one sec, Proceedings of the National Academy of Sciences 120 (2023) e2213114120. doi:10.1073/pnas.2213114120.

[39] M. C. C. Bomfim, S. I. Kirkpatrick, L. E. Nacke, J. R. Wallace, Food literacy while shopping: Motivating informed food purchasing behaviour with a situated gameful app, in: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, Chi '20, Association for Computing Machinery, New York, NY, USA, 2020, pp. 1–13. doi:10.1145/3313831.3376801.

[40] K. Degirmenci, T. M. Katolla, M. H. Breitner, How Can Mobile Applications Reduce Energy Consumption? An Experimental Investigation of Electric Vehicles, ECIS 2015 Completed Research Papers (2015).

[41] J. Park, H. Lee, S. Park, K.-M. Chung, U. Lee, GoldenTime: Exploring system-driven timeboxing and micro-financial incentives for self-regulated phone use, in: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, Chi '21, Association for Computing Machinery, New

York, NY, USA, 2021. doi:10.1145/3411764.3445489.

[42] V. Allom, B. Mullan, Two inhibitory control training interventions designed to improve eating behaviour and determine mechanisms of change, Appetite 89 (2015) 282–290. doi:10.1016/j.appet.2015.02.022.

[43] D. Dunbar, M. Proeve, R. M. Roberts, Problematic internet usage: Can commitment and progress frameworks help regulate daily personal internet use?, Clinical Psychologist 28 (2024) 131–141. doi:10.1080/13284207.2024.2322940.

[44] N. Ackermann, L. D. Cameron, J. Maki, C. R. Carter, Y. Liu, H. Dart, D. J. Bowen, G. A. Colditz, E. A. Waters, Mental imagery-based self-regulation: Effects on physical activity behaviour and its cognitive and affective precursors over time, British Journal of Health Psychology 27 (2022) 484–500. doi:10.1111/bjhp.12558.

[45] S. N. Loeffler, J. Stumpp, S. Grund, M. F. Limberger, U. W. Ebner-Priemer, Fostering self-regulation to overcome academic procrastination using interactive ambulatory assessment, Learning and Individual Differences 75 (2019). doi:10.1016/j.lindif.2019.101760.

[46] R. F. Kizilcec, J. Reich, M. Yeomans, C. Dann, E. Brunskill, G. Lopez, S. Turkay, J. J. Williams, D. Tingley, Scaling up behavioral science interventions in online education, PNAS Proceedings of the National Academy of Sciences of the United States of America 117 (2020) 14900–14905. doi:10.1073/pnas.1921417117.

[47] K. M. Friederichs, N. B. Jostmann, J. Kuhl, N. Baumann, The art of getting things done: Training affective shifting improves intention enactment, Emotion 23 (2023) 651–663. doi:10.1037/emo0001128.

[48] S. M. Herzog, R. Hertwig, Boosting: Empowering Citizens with Behavioral Science, Annual Review of Psychology 76 (2025) 851–881. doi:10.1146/annurev-psych-020924-124753.

[49] L. Michels, J. Ochmann, K. Schmitt, S. Laumer, V. Tiefenbeck, Salience, transparency, and self-nudging: A digital nudge to promote healthier food product choices, European Journal of Information Systems 33 (2024) 717–747. doi:10.1080/0960085X.2023.2229787.

[50] M. L. Lee, A. K. Dey, Real-time feedback for improving medication taking, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Chi ’14, Association for Computing Machinery, New York, NY, USA, 2014, pp. 2259–2268. doi:10.1145/2556288.2557210.

[51] R. F. Baumeister, M. Gailliot, C. N. DeWall, M. Oaten, Self-Regulation and Personality: How Interventions Increase Regulatory Success, and How Depletion Moderates the Effects of Traits on Behavior, Journal of Personality 74 (2006) 1773–1802. doi:10.1111/j.1467-6494.2006.00428.x.

[52] M. Inzlicht, E. Berkman, Six Questions for the Resource Model of Control (and Some Answers), Social and Personality Psychology Compass 9 (2015) 511–524. doi:10.1111/spc3.12200.

[53] J. Lee, E. Walker, W. Burleson, M. Kay, M. Buman, E. B. Hekler, Self-experimentation for behavior change: Design and formative evaluation of two approaches, in: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, Chi ’17, Association for Computing Machinery, New York, NY, USA, 2017, pp. 6837–6849. doi:10.1145/3025453.3026038.

[54] L. Degroote, A. De Paepe, I. De Bourdeaudhuij, D. Van Dyck, G. Crombez, Effectiveness of the mHealth intervention ‘MyDayPlan’ to increase physical activity: An aggregated single case approach, The International Journal of Behavioral Nutrition and Physical Activity 18 (2021). doi:10.1186/s12966-021-01163-2.

[55] T. Qian, M. A. Russell, L. M. Collins, P. Klasnja, S. T. Lanza, H. Yoo, S. A. Murphy, The Micro-Randomized Trial for Developing Digital Interventions: Data Analysis Methods, 2020. doi:10.48550/ARXIV.2004.10241.

[56] F. Stock, R. Hertwig, P. Lorenz-Spreen, An Accuracy Self-Nudge to Reduce Misinformation Sharing Online, 2023. doi:10.31234/osf.io/awj97.

[57] A. Pinto, J. E. Steinglass, A. L. Greene, E. U. Weber, H. B. Simpson, Capacity to Delay Reward Differentiates Obsessive-Compulsive Disorder and Obsessive-Compulsive Personality Disorder, Biological Psychiatry 75 (2014) 653–659. doi:10.1016/j.biopsych.2013.09.007.