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Digital Human Representations for Health Behavior Change: A Structured Literature Review

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Abstract:

Organizations have increasingly begun using digital human representations (DHRs), such as avatars and embodied agents, to deliver health behavior change interventions (BCIs) that target modifiable risk factors in the smoking, nutrition, alcohol overconsumption, and physical inactivity (SNAP) domain. We conducted a structured literature review of 60 papers from the computing, health, and psychology literatures to investigate how DHRs' social design affects whether BCIs succeed. Specifically, we analyzed how differences in social cues that DHRs use affect user psychology and how this can support or hinder different intervention functions. Building on established frameworks from the human-computer interaction and BCI literatures, we structure extant knowledge that can guide efforts to design future DHR-delivered BCIs. We conclude that more field studies are needed to better understand the temporal dynamics and the mid-term and long-term effects of DHR social design on user perception and intervention outcomes.

Keywords: Avatar, Behavior Change, Embodied Agent, Digital Human Representation, Social Cues.

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1 Introduction

Non-communicable diseases, such as heart diseases and type 2 diabetes, are the leading cause of premature deaths worldwide with 16 million cases yearly (World Health Organization, 2020). The World Health Organization has focused its attempts to prevent non-communicable diseases by targeting individual health behaviors related to four major risk factors: smoking, nutrition, alcohol overconsumption, and physical inactivity (i.e., the so-called SNAP factors) (World Health Organization, 2020). To facilitate change in people's health behavior, health professionals carry out so-called behavior change interventions (BCIs); that is, "interventions designed to affect the actions that individuals take with regard to their health" (Cutler, 2004, p. 2).

Over the past two decades, information systems have created novel ways to support health professionals in delivering BCIs and enable population-wide health behavior change at scale (Michie et al., 2017; Noorbergen et al., 2019). Anthropomorphic design features trigger users' psychological processes and facilitate the formation of a socio-technical relationship between the user and the system (Kim & Sundar, 2012a; Pfeuffer et al., 2019). Variations in social design affect users' perceptions differently and can influence their resulting behavior (Yee & Bailenson, 2007). In this vein, to further increase a system's impact on user behavior, research introduced technology-mediated BCIs that specifically adopt social design elements. For example, researchers have used social robots to facilitate behavior change through natural interaction with users (Kidd & Breazeal, 2008; Olaronke et al., 2017; Złotowski et al., 2015). Another approach that does not require physical objects and, therefore, integrates into everyday life through existing interfaces (e.g., smartphones, websites) involves using digital human representations (DHRs), such as avatars (controlled by humans) and embodied agents (controlled by algorithms) (Aljaroodi et al., 2019; Noorbergen et al., 2019). Indeed, many studies have shown that both avatars (e.g., Peña et al., 2016; Song et al., 2013) and embodied agents (e.g., Bickmore et al., 2013b; Lisetti et al., 2013) can facilitate health behavior change. However, variations in DHRs' social role, dynamics, physical appearance, and other factors have been associated with different behavioral outcomes. Thus, we need to understand how design decisions on DHRs social features, or social cues, influence whether BCIs succeed. In this regard, we can understand DHR social cues as stimuli for future action, similar to how people process social cues in real-world interactions. Users then use the DHR's social cues—mostly instinctively—to form a social relationship with the DHR (Feine et al., 2019; Fogg, 2003).

Several literature reviews provide important syntheses and guidance on applying DHRs for health behavior change. For instance, previous reviews have established that embodied agents can be a valuable tool for electronic health (eHealth) (Montenegro et al., 2019) and argued that differences in how one designs embodied agents (ter Stal et al., 2020) and avatars (Clark et al., 2019) may impact participation rates and, thus, intervention outcomes. While they have shown that DHRs can successfully facilitate technology-mediated BCIs, no review has systematically reviewed the myriad existing social design features up to now. However, as technology-mediated interventions strongly rely on socio-technical relationships, we need to explore the impact that design features have on user perceptions and, in turn, how such perceptions influence intervention outcomes. We thus propose the following research question:

> **RQ:** What are the social design features, targeted psychological constructs, and behavior-change interventions in digital human representations for SNAP health behavior change in healthy populations?

In this paper, we address this question by reviewing the academic literature. In particular, we synthesize design knowledge available from existing studies that have empirically tested the impact of specific social design features of DHRs on the outcomes of BCIs in the SNAP domain. Accounting for the targeted research's interdisciplinary nature, we searched 10 different databases. We identified 60 relevant papers published between January 2005, and February 2021, in computing, health, and psychology outlets. With our review, we summarize in a structured manner the most widely employed social design features, the targeted constructs in user perception, the employed BCI functions, and the evoked changes in users' behaviors. We also discuss knowledge gaps and directions for future research.

2 Theoretical Background

2.1 Related Reviews

Existing reviews demonstrate that DHRs have attracted broad use in different application areas, such as education and health (Aljaroodi et al., 2019), and that they can play a promising role in health applications (Clark et al., 2019; Kramer et al., 2020; ter Stal et al., 2020). Such reviews include work that has summarized DHR adoption in different fields for health promotion, disease management, and clinical psychology (Laranjo et al., 2018; Montenegro et al., 2019; Provoost et al., 2017). In terms of DHR design, reviews on embodied agents (ter Stal et al., 2020) and avatars (Clark et al., 2019) emphasize looks, visual behavior, and, for embodied agents, language output as key factors that influence behavior in the eHealth context (Clark et al., 2019; ter Stal et al., 2020). In their scoping review of agents for coaching healthy lifestyles, Kramer et al. (2020) identified the need to 1) integrate users in the design process and 2) clarify the underlying theoretical foundations and persuasive tactics in evaluation reports. However, to the best of our knowledge, no existing review has summarized the most widely employed social design features in DHRs, the targeted constructs in user perception, the employed behavior-change intervention functions, and the evoked changes in users' health behaviors.

2.2 Foundations of Health Behavior Change

Behavior change interventions (BCIs) refer to "coordinated sets of activities designed to change […] behavioral patterns" (Michie et al., 2011, p. 1). Various theories for behavior change exist (Pinder et al., 2018). Stage-based models, such as the transtheoretical model of behavior change (Prochaska & Velicer, 1997), suggest that behavior change happens in discrete stages that the individual needs to undergo step by step. The perception of different social variables during the interventions, such as perceived risk or personal relevance, thus needs to be tailored to the recipient's stage of change (Lippke & Ziegelmann, 2008). Continuum models, such as social cognitive theory (Bandura, 1986), combine linear predictors (e.g., intentions or attitudes) to assess behavior likelihood and provide possible determinants for behavior change (Lippke & Ziegelmann, 2008). As a common ground, the theories describe that BCIs happen in a social context and socio-cognitive variables determine whether an intervention succeeds or fails. However, "[e]ven when one or more models or theories are chosen to guide the intervention, they do not cover the full range of possible influences" (Michie et al., 2011, p. 2). As a synthesis based on various existing theories, Michie et al. (2014) proposed the behavior change wheel as a systematic guide for BCI design. Researchers have used it extensively in the health promotion domain due to its simplicity and accessibility (Noorbergen et al., 2019).

The behavior change wheel comprises three layers: 1) the sources of behavior combined in the capability, opportunity, motivation, behavior (COM-B) model, 2) nine behavior-change intervention functions to affect the behavior, and 3) policies that enable the BCIs. We focus on the first two, as the definition of policies falls outside the scope of designing a DHR-based BCI. The COM-B model posits that the continuous interaction between an individual's capability, opportunity, and motivation generates behavior and vice-versa (see arrows in Figure 1). Capability describes the physical skills, stamina, or strength (e.g., ability to exercise), and psychological skills, knowledge, or mental strength one needs to perform the behavior or engage in the necessary mental processes (e.g., healthy nutrition knowledge) (Michie et al., 2014). Opportunities can be physical, provided by the surroundings, such as time, triggers, resources, locations, barriers (e.g., an environment rich in healthy foods), or social in nature, such as interpersonal influences, social cues, norms (e.g., social contacts discouraging smoking) (Michie et al., 2014). Motivation can evolve from reflective processes (i.e., planning and evaluation) or happen due to automatic processes (i.e., reflexes or emotions) (Michie et al., 2014). BCIs can affect the COM-B elements. They can target one or multiple COM-B elements and build on intervention functions (i.e., coercion, education, enablement, environmental restructuring, incentivization, modeling, persuasion, restriction, and training) (Michie et al., 2014, 2011). Figure 1 provides a simplified illustration of the relationship between BCIs and COM-B. One needs to tailor BCIs to users for them to work effectively (Kreuter et al., 2013). Such tailoring may involve simple measures, such as personalizing communication to the user's name (Kankanhalli et al., 2021). However, one can also use advanced measures, such as adapting feedback messages or the BCI provider's gender (Lisetti, 2009) or tailoring the game strategy in a healthy eating game to the user's personality (Orji et al., 2017). Importantly, design aesthetics and unobtrusiveness influence persuasiveness, dialogue support, credibility, and, finally, user adoption (Lehto et al., 2012). Thus, intervention uptake depends not only on the intervention design and targeted behavior but also on the DHR's social design, which refers to its role, looks, social behavior, and user perceptions thereof.

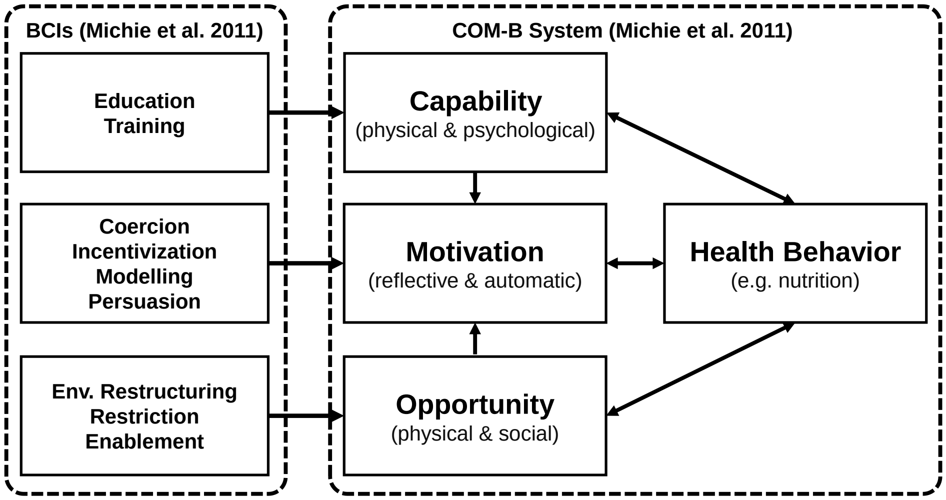


Figure 1. BCIs and Their Influence on the COM-B Model (Adapted from Michie et al., 2011)

2.3 Social Design Foundations of Digital Human Representations

For technology-based BCIs, the user-technology relationship plays a critical role in short-term compliance and long-term adherence (Bickmore et al., 2005b; Bickmore et al., 2010). In this context, the computers-are-social-actors paradigm states that users mindlessly apply social heuristics in human-computer interaction, which triggers instinctive, automatic responses in the users, and the development of a socio-technical relationship between user and involved system (Fogg, 2003). With their implicit human features, DHRs provide social cues that users know from real-world interactions and instinctively draw on to build social relationships (Feine et al., 2019; Fogg, 2003). These relationships can motivate users to perform a certain behavior (Fogg, 2003). For example, in their study, Cafaro et al. (2016) found that users in a greeting encounter with a digital museum guide agent quickly developed an initial impression of the agent's personality and attitude, and that this impression influenced the likelihood and frequency with which users would further use the agent. Furthermore, they found that adapting the agent to the users increased interactions with the agent (Cafaro et al., 2016). Thus, we need to understand the underlying psychological mechanisms for users to increase their readiness to interact with an agent or avatar to facilitate DHR-mediated behavior change.

Social cues refer to design features that present a salient information source and trigger social reactions in users (Feine et al., 2019; Fogg, 2003). Because individuals process social cues automatically, the cues influence behavior mostly unconsciously (Fogg, 2003). Fogg (2003) suggested that one can separate social cues in computing into five primary types: language (e.g., the wording of written or spoken messages), physical (e.g., body shape, clothing), psychological (e.g., emotions, motivations), social dynamics (e.g., respecting social rules and rituals), and social roles (e.g., coach, friend)[1]. These cues inherently form the foundation for how users perceive DHRs, such as their attractiveness, personality, and persuasiveness (Fogg, 2003). For example, interaction speed and emotionality impact how users perceive an agent's empathy (Bickmore et al., 2005b; Klaassen et al., 2013a; Lisetti et al., 2013). Further, the facial similarity between a user and an agent can affect the extent to which the user perceives the agent as helpful (van Vugt et al., 2008). The Proteus effect can cause users to adapt their behavior to better match their avatar's social design (Yee & Bailenson, 2007).

We identify four main components that conceptualize the relationship between DHR design and behavior change (see Figure 2). First, the availability of and interplay between social cues form a DHR's social design.

[1] One can distinguish several self-concepts (Higgins, 1987). Self-avatars can function as 1) the actual-self (i.e., as representing the user's actual personal attributes), 2) the ideal-self (i.e., as representing the user's hopes and aspirations), 3) the future-self (i.e., as modeling the user's future state if they continue a certain behavior), or 4) the ought-self (i.e., as representing the expectations or responsibilities other people impose on the user).

Second, via changes in user perception (e.g., perceived similarity), a DHR's social design affects the social relationship between the user and the DHR (Feine et al., 2019). Third, changes in user perception may support or hinder the extent to which a BCI can effectively change a user's capability, opportunity, motivation, and, finally, behavior (Michie et al., 2011). Next, we build on these four components to organize the results from our structured literature review. Specifically, we elaborate on different design variations, their effects on user psychology, and the resulting influences on BCIs and behavioral outcomes.

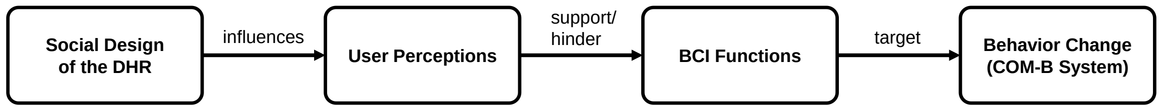
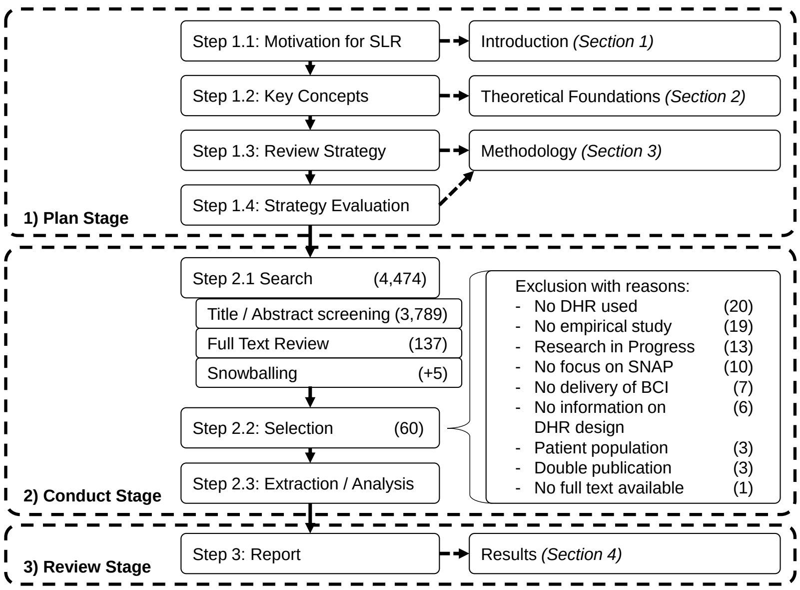


Figure 2. Structure Underlying the Present Review

3 Methodology

In line with our overarching research question, we focus on studies that have evaluated DHRs empirically with human users and focused on facilitating health behavior change in the SNAP domain. Following Kitchenham and Charters' (2007) guidelines, we divided the review process into the stages of plan, conduct and review (see Figure 3).



Database	Search Results
AIS eLibrary	109
SpringerLink	1,269
Scopus	1,273
IEEE Xplore	7
Web of Science	35
PubMed	106
ACM Digital Library	358
Taylor & Francis Online	261
Wiley Online Library	236
ScienceDirect [2]	820
- Duplicates	685
Total	3,789

Figure 3. Stages of the Structured Literature Review, Paper Sections, and Search Results per Database

3.1 Study Selection Criteria

We include papers that 1) used at least one DHR of the self, a digital doctor, counselor, coach, friend, or similar human role (i.e., excluding animals, plants, phantasy figures, and physical robots), 2) focused on SNAP behavior change for healthy populations (excluding papers that focused on patient populations with special requirements often connected to chronic diseases such as diabetes, Parkinson's disease, or HIV; despite being a chronic condition, we include obesity due to its close connection to nutrition and physical activity), and 3) tested the DHR in an empirical setting with humans (excluding papers that measured behavioral patterns but did not focus on changing behavior and/or did not empirically evaluate the DHR in human populations). We included all peer-reviewed journals and full-text conference publications written in English.

3.2 Search Strategy

We conducted an initial search on Google Scholar to explore the field using the search query "(avatar OR 'embodied agent') AND 'behavior change' AND health". We reviewed the obtained results and noted relevant terms to develop our search term. We extended the search string with terms describing the role that DHRs took, such as virtual/digital advisor or virtual/digital coach. Furthermore, we concretized the search string on SNAP factors by including terms often used in concordance with the single behavioral patterns associated with SNAP. After selecting 10 well-established databases for literature in the information systems and medical context (i.e., AIS eLibrary, SpringerLink, Scopus, IEEE Xplore, Web of Science, PubMed, ACM Digital Library, Taylor & Francis Online, Wiley Online Library, and ScienceDirect), we performed a full-text search in February 2021[2]. We used search alerts to stay updated on new findings from the databases.

The full-text search resulted in 3,789 unique papers in total. The second and fourth authors independently screened titles, abstracts, and keywords against the defined study selection criteria (agreement rate: 94.62%). They resolved discrepancies via discussion with the first author (204 papers: 79 included, 125 excluded). The second author reviewed the remaining 137 papers in full and added five additional papers via the snowballing method. In the full-text review, the second author excluded 82 papers based on the reasons shown in Figure 3. The second and fourth authors then analyzed the findings of the final corpus of 60 papers along with the components of DHR design, psychological constructs, intervention types, and behavior change (see Figure 2). Appendix A provides an overview of our results. To evaluate and ensure the results' quality, the first, second, and fourth authors complementarily conducted a risk of bias analysis (see Appendix B).

4 Results

In this section, we present the results from our review. We describe DHR's social design variations, which we cluster according to Fogg's (2003) five principle social cue types. We found that the social design variations have a multi-faceted influence on user perceptions and intervention uptake. We report the user perceptions researchers investigated with intervention functions (Michie et al., 2014). Finally, we summarize the behavioral outcomes resulting from the behavior change interventions (BCIs).

4.1 Results on Social Design of the DHR

4.1.1 Social Role

Most papers (31 papers, 51.7%) used embodied agents closely followed by avatars (25 papers, 41.7%). Only four studies (6.7%) combined both DHR types. For example, users meet with agents via self-avatars in a health game (Kim & Sundar, 2012b; Thomas et al., 2015). We consider these papers as belonging to the avatar papers henceforth.

All 29 avatar papers employed self-avatars. Six papers additionally compared the influence of other-avatars as opposed to self-avatars explicitly (Ahn, 2015; Ahn et al., 2014a; Fox & Bailenson, 2009; Navarro et al., 2020b; Peña et al., 2016; Peña & Kim, 2014). One study used self-avatars and other-avatars for users to interact with a real-life nutrition or fitness professional for one hour per week (Johnston, Massey, & DeVaneaux, 2012). Four studies found that tailoring health messages with self-avatars, as compared to other-avatars, increases BCI effectiveness (Ahn, 2015; Ahn et al., 2014a; Fox & Bailenson, 2009; Navarro et al., 2020b). They found both the self-avatar's and other-avatar's body size to influence physical activity. Avatar users were most active when both avatars looked physically fit, while showing an obese opponent to a user with a normal self-avatar resulted in the least activity (Peña et al., 2016; Peña & Kim, 2014).

[2] We used the following completed search string: "(avatar OR 'embodied agent' OR 'embodied conversational agent' OR 'mirrored self' OR 'virtual relational agent' OR 'digital adviser' OR 'digital advisor' OR 'digital coach' OR 'digital health coach' OR 'digital human representation' OR 'digital self representation' OR 'virtual adviser' OR 'virtual advisor' OR 'virtual coach' OR 'virtual health coach' OR 'virtual human representation' OR 'virtual self representation') AND ('behavior change' OR 'behaviour change' OR 'change in behavior' OR 'change in behaviour' OR 'behavioral change' OR 'behavioural change' OR 'lifestyle change') AND (smok* OR cigarette OR tobacco OR nutrition OR eat* OR food OR diet* OR fruit OR vegetable OR alcohol OR drink* OR 'physical activity' OR 'physical inactivity' OR sport OR exercise OR walk* OR obesity OR obese OR 'weight loss' OR overweight OR 'healthy lifestyle' OR sedentary OR 'health promotion' OR exergam*)". Due to length restrictions for the search string on ScienceDirect, we had to split the search string into multiple parts and conduct multiple searches. We then filtered duplicates that occurred during searches on ScienceDirect before joining the search results with results from other databases.

Various self-concepts emerged in self-avatars design. While two studies focused on actual-self (Napolitano et al., 2013; Thompson et al., 2016), three studies compared future- and actual-self (Fuchs et al., 2019; Schmeil & Suggs, 2014; Song et al., 2013), five compared actual- and ideal-self (Jin, 2009; Johnston et al., 2012; Kim & Sundar, 2012b; Lyles et al., 2017; Navarro et al., 2020a), and two compared ought-/future-, actual-, and ideal-self (Koulouris et al., 2020; Sah et al., 2017). However, most self-avatar studies did not specify the self-concept (17 of 29 / 58.6%). Sah et al. (2017) found that the ought-self promoted health consciousness more strongly than the ideal-self and actual-self. At the same time, the ideal-self yielded higher immersion than the actual-self (Jin, 2009). The future-self-avatar functions as a personal model that illustrates the future consequences of a current behavior. It positively impacted interventions when projecting negative (Song et al., 2013) and positive (Schmeil & Suggs, 2014) future consequences. Multiple studies took different approaches towards who created the user's avatar: the user (e.g., Jin, 2009; Lyles et al., 2017) or the research teams with no modification from the user (e.g., Fox & Bailenson, 2009; Fox et al., 2009; Napolitano et al., 2013). However, no study in our review corpus explicitly investigated the effect that avatar creation may have on bonding. However, findings in the studies that compared actual-self-avatars to ideal-self-avatars pointed in the direction that providing the user with the opportunity to create their own avatar is beneficial (e.g., Sah et al., 2017).

We found an even more diverse range of social roles for embodied agents. They can take the role of a friend (Bickmore et al., 2005b) who accompanies the behavior change by socially supporting positive behavior and helping when the user has a bad mood. They can act as a coach or a counselor (Abdulla et al., 2018) who provides recommendations and advice on how to change health behavior. They can function as a health professional, such as a doctor (Klaassen et al., 2013a), who provides personal health assessment. They can also act as someone who opposes health behavior change (Thomas et al., 2015), such as in a social eating practice situation where the agent tries to entice the user to eat unhealthy foods.

Further, these roles have important overlaps. For example, a counselor can also try to form a friendly relationship with the user by focusing on "hard facts" and showing interest in the user's private life and empathy (Lisetti et al., 2013). Most agent studies (28 of 31 agent studies / 90.3%) employed counselor or coach agents. However, at the same time, many DHRs try to build a social relationship with the user, such as by engaging in social talk (Bickmore et al., 2005a). Thus, other social design aspects, such as language cues (e.g., medical terminology, social talk) and physical cues (e.g., medical clothing, stethoscope), also shape a DHR's social role.

For avatars, a DHR's gender mostly matched the user's gender. For agents, most studies employed a female role (25 of 31 / 80.6%). Five agents (16.1%) matched the user's gender, and one was male (3.2%). Creed and Beale (2012) argued that users perceive female agents more favorably due to increased perceived attractiveness. Joo and Kim (2017) conjectured that users "would respond more sensitively toward an obese female avatar than an obese male avatar" (p. 459). However, some researchers observed that matching agent gender (e.g., male agents for male users) yielded higher persuasiveness, although the effect was more pronounced for female users (Guadagno et al., 2007). Most agents are adults of medium age (i.e., not seniors), while studies adapted self-avatars to the user's age. Notably, no study discussed the DHR's age (e.g., gray/thin hair, wrinkles).

4.1.2 Social Dynamics

Following social dynamics and "knowing" unwritten patterns of interpersonal interaction can support the social user-artifact bond (Fogg, 2003). Greetings and social questions about the user's feelings when an interaction begins (e.g., Bickmore et al., 2005a; Gardiner et al., 2017) and adapting content and coloring to culture-specific features (Zhou, Zhang, & Bickmore, 2017) represent possibilities to adapt a DHR's social dynamics. Studies reported cultural adaption for Hispanic (e.g., King et al., 2013), African-American (e.g., Bickmore et al., 2005a), Indian (Murali et al., 2020), and Chinese populations (Zhou et al., 2017) and formulated general guidelines for Arabic DHRs (Aljaroodi et al., 2020). Nevertheless, when using culturally adapted DHRs, designers need to carefully weigh cultural cues against other factors. As Zhou et al. (2017) stated:

> *[S]ince regular exercise, the topic discussed during the interaction, is not traditionally a popular theme in Chinese culture, young Chinese adults moving to the U.S. may perceive the American character as more knowledgeable, and more authoritative in the field of exercise coaching, and thus would be more willing to follow the advice offered by the American figure* (p. 94).

Similarly, Murali et al. (2020) found that cultural tailoring works most successfully when appearance (i.e., physical cues) concurs with a culturally adopted argumentation as reflected in language and psychological cues. Taken as a whole, these findings emphasize the interrelatedness between social cues.

For embodied agents, system designers need to decide who initiates the interaction and who controls its flow (i.e., turn-taking; user or agent). In most studies, users began the conversation according to the study protocol. Other options include an acoustic signal (Bickmore et al., 2007) or a textual countdown (Fuchs et al., 2019). The agent begins by greeting the user and waits for user input to prepare the response. During the interaction, the agent may provide hints when waiting for user replies, such as by using winks towards possible answers (Creed & Beale, 2012). No study we reviewed explicitly investigated the potential effects that turn-taking has on BCI effectiveness. However, different turn-taking behaviors correspond with different perceptions of authority or dominance (Beňuš et al., 2011) and, thus, have the power to influence user perceptions and behaviors.

We also observed different overall embodiment levels, that is, body parts that the user can see (Aljaroodi et al., 2019). With only two exceptions—one face-only (Peng, 2009) and one upper-body avatar (Andrade et al., 2016)—the avatar studies in our review all used full-body embodiments. For embodied agents, we found a more diverse picture: 18 upper-body (e.g., Bickmore et al., 2005a; Gardiner et al., 2017; Olafsson et al., 2019), seven face-only (e.g., Creed & Beale, 2012; de Rosis et al., 2006; Vainio et al., 2014), and six full-body agents (e.g., Oyibo et al., 2018; van Vugt et al., 2006, 2009). It is conceivable that the embodiment level may help DHRs form social relationships with users by influencing the perceived closeness and intimacy with the DHR if applied correctly and in correspondence to users' social expectations. However, no paper we reviewed systematically investigated the influence that embodiment level has on the social relationship to the agent or the intervention outcome.

4.1.3 Physical

Overall, 36 papers (60%) employed three-dimensional (3D) DHRs, while 24 (40%) relied on two-dimensional (2D) visualizations. In particular, the avatar studies primarily used 3D DHRs (26 of 29 avatar papers, 89.7%). Studies further varied in photorealism, that is, the DHR's similarity to a photographic image of a human. The reviewed studies covered the full range of this continuum from simple comic-like bodies (van Vugt et al., 2006) to comic-like DHRs personalized with photos of a user's face (Song et al., 2013), 3D photorealistic agents (Zhou et al., 2017), and self-avatars based on 3D body scans (Lyles et al., 2017).

Furthermore, 50 studies (83.3%) used some form of DHR dynamics (i.e., fluently changing their position, facial expression, or other dynamic animation). Interestingly, multiple studies investigated the effect that DHR movement had on users. They provided evidence that a DHR performing a sportive activity can motivate users to exercise better than a loitering DHR (Fox & Bailenson, 2009; Joo & Kim, 2017; Morie et al., 2013; Schmeil & Suggs, 2014).

For self-avatars, body shape often aligns with the employed self-concept (see Section 4.1.1) with users commonly associating their ideal-self and, hence, their self-avatar as being slenderer. Consequently, multiple studies showed that users whom a slenderer self-avatar represented would show more physical activity, motivation to exercise, and healthier nutrition behavior (Li et al., 2014; Peña et al., 2016; Peña & Kim, 2014). However, as Joo and Kim (2017) noted, an avatar's body shape should align with its behavior/movements. For other-avatars, body shape exhibited a higher impact for female users than for male users. Studies identified the highest physical activity levels in situations with both a thin self-avatar and thin other-avatar (Peña et al., 2016; Peña & Kim, 2014). On the contrary, larger body sizes achieved higher user preference and usage intentions (van Vugt et al., 2006, 2009).

Concerning clothing, most DHR wore workday clothes or sportswear aligned to the social role and context. Agents with a health professional's role wore medical clothing, which included a stethoscope to support the social role (Klaassen et al., 2013a, 2013b; Lisetti et al., 2015). For avatars, Navarro et al. (2020b) found users to engage in more physical exercise if their avatar wore sports rather than formal clothing. Further, some avatar studies allowed users to customize avatar clothing (Johnston et al., 2012; Kim & Sundar, 2012b; Sah et al., 2017; Thompson et al., 2016; Waddell et al., 2015). Although users often request customization (Lyles et al., 2017), Waddell et al. (2015) reported that it did not positively influence physical activity levels. Controversially, previous research on avatars suggests that customization impacts identification with the self-avatar. It translates into more motivation (Behm-Morawitz, 2013; Birk et al., 2016) and helps reduce attrition over time (Birk & Mandryk, 2018).

4.1.4 Language

We first focus on the language options for user input. For embodied agents, the majority of studies (25 of 31 agent-only studies / 80.6%) implemented user input as choosing from a set of predefined answers (e.g., Bickmore et al., 2005a; King et al., 2020, 2013; Mohan et al., 2020). Olafsson et al. (2019) showed that the valence (positive/negative connotations) of the available answers influenced users' confidence in performing the targeted behavior, although users preferred to have both types of answers available. Six studies allowed free text input, although most either did not process the answers at all or did so with simple pattern matching (Bickmore et al., 2005b; Creed & Beale, 2012; Friederichs et al., 2015). Only one recently published study employed natural language processing to respond to users' written input (Maher et al., 2020). In so-called Wizard-of-Oz studies (i.e., where a researcher controls the agent), researchers allowed users to make their dialogue selection via voice input (Schulman & Bickmore, 2009) or responded to textual user input by selecting dialog options (de Rosis et al., 2006). Researchers have also successfully tested system-processed voice input based on natural language processing (Yasavur et al., 2014). By contrast, most avatar-only studies (23 of 25, 92%) did not include textual user input, though some instead relied on a keyboard to control the self-avatar. Two avatar studies allowed users to communicate with each other using text input (Behm-Morawitz et al., 2016; Johnston et al., 2012).

For language output to users, studies used both written and spoken messages. For avatars, researchers used posters, menus, or other written media for verbal communication (Johnston et al., 2012; Kim & Sundar, 2012b). Some studies visualized communication with other-avatars or embodied agents using text fields (e.g., Klaassen et al., 2013a; Peng, 2009) or speech bubbles next to the DHR (e.g., Friederichs et al., 2015; Vainio et al., 2014; van Vugt et al., 2006). For spoken messages (typically in the user's native tongue), studies implemented a voice using either prerecorded messages (Creed & Beale, 2012) or synthetic text-to-speech systems (e.g., Bickmore et al., 2005a; Lisetti et al., 2013; Yasavur et al., 2014). Various factors, such as accent, pitch, speed, and tone, require consideration. For example, the perceived politeness of agent's sound influenced short-term compliance and long-term adherence concerning the targeted behavior (Bickmore et al., 2007). Reading the messages letter by letter led to user complaints about bad glanceability (Klaassen et al., 2013b). Further, conversations with auditory output via speakers have received criticism for privacy reasons (Bickmore et al., 2007). To avoid private information being heard by bystanders, one study asked users to wear headphones during the intervention (King et al., 2013).

4.1.5 Psychological

Psychological cues lead users to perceive DHRs to have emotions or a personality (Fogg, 2003). These cues include using social conversation in a targeted manner (e.g., asking users about their current feelings), gestures, mimics, and different verbal strategies of presentation (e.g., using humor and sarcasm). With this form of simulated social behavior, the DHR imitates behavioral patterns from human interaction and conveys emotions to users naturally (Creed & Beale, 2012). As an example, agents often chat with users about their feelings and everyday experiences (e.g., Lisetti et al., 2013; Olafsson et al., 2019; Zhou et al., 2017), which can help agents form a social relationship with users (Bickmore et al., 2005b; Bickmore et al., 2010). However, repetitive dialogues and clothing can evoke negative reactions and adverse effects on actual behaviors (Bickmore et al., 2010). Designers need to ensure that the social behavior matches the other design cues. For instance, Murali et al. (2020) found employing a culturally adapted argumentation style (e.g., collectivist or individualistic nature of the cultural background) to be more effective when the agent's physical appearance also corresponded to the same cultural background.

As a verbal strategy, humor in agents (e.g., jokes, sarcasm) yields positive user feedback (Olafsson et al., 2019; Peng, 2009). Importantly, verbal strategies require the corresponding non-verbal behavior, such as smiling when telling jokes or a concerned look when talking about problems (Creed & Beale, 2012; Lisetti et al., 2013). Compared to purely text-based interactions, an empathic agent showing non-verbal behavior can support intervention outcomes (Lisetti et al., 2013). Non-verbal behavior to express empathy includes facial expressions (e.g., gaze, lip movements) and gestures (e.g., pointing with the finger, shrugging the shoulders) related to the conversational content (e.g., Bickmore et al., 2005a; Creed & Beale, 2012). To help a DHR mimic non-verbal behavior, designers can also use video-based expression analysis to detect the user's mental state and adapt the agent's facial expressions accordingly (Lisetti et al., 2013). For avatars, most studies used neutral facial expressions and gestures. While Kim and Sundar (2012b) allowed users to change their self-avatars' gestures, Fuchs et al. (2019) used facial expressions to visualize future consequences of health behavior.

As we have seen, studies have used social cues in various combinations and variations (social role, social dynamics, physical, language, psychological) to design DHRs in the SNAP behavior change domain. Importantly, the combination of all available cues forms a user's perception and impression, rather than only the interpretation of a single cue (Creed & Beale, 2012; Fogg, 2003). Hence, designers need to consider the interplay between all primary social cue types during the DHR design phase. For example, increasing the realism of an agent's physical cues will also result in higher user expectations concerning DHR's psychological cues. Further, the interplay between social cues and their relevance to the user psychology via mindful or mindless processing influences whether users form a socio-technical relationship with DHRs and whether users change their behavior (Ahn et al., 2014; Bandura, 1986; Sah et al., 2017). For messages with lower personal importance in particular, constructs such as trustworthiness, knowledgeability, or likeability become more important in evaluating the message and persuading users (Schulman & Bickmore, 2009). For this reason, we now focus on the constructs that research has tested concerning user psychology and their effect on behavior change interventions (BCIs).

4.2 Results on User Perception

Table 1 summarizes the most frequently investigated constructs (i.e., at least three studies used them). Generally, we see that the studies have tested all constructs with embodied agents, but they have considered only attractiveness, enjoyment, persuasiveness, satisfaction, presence, similarity, and social distance for avatars. We can attribute this finding to the fact that most avatar studies focused on questions concerning the avatar's graphical design or social role. In contrast, agent studies included constructs predominantly related to verbal behavior in the interaction between user and agent. Furthermore, when synthesizing the results in previous studies, the interplay between and combination of constructs emerged as an important consideration for DHR design. Thus, in this section, we analyze a subset of the different psychological constructs, their interplay with each other, and the influence that DHR design has on these constructs.

Table 1. Psychological Constructs Evaluated in the 60 Papers in the Review

Construct (closely related constructs)	Explanation	Usage
Attractiveness (aesthetics)	How much the user perceives the DHR to be visually appealing	**EA**: Klaassen et al. (2013a), van Vugt et al (2006) **AV**: Jin (2009) **EA+AV**: Kim & Sundar (2012b)
Credibility	How believable the DHR is to the user	**EA**: de Rosis et al. (2006), King et al. (2013) Klaassen et al. (2013b), van Vugt et al. (2006, 2009) **EA+AV**: Peng (2009), Thomas et al. (2015)
Ease of use	How easy to use the user perceives the DHR to be	**EA**: Abdullah et al. (2018), Bickmore et al. (2005a), Bickmore et al. (2013s); King et al. (2013), Lisetti et al. (2013), Mazzotta et al. (2009), Yasavur et al. (2014), Zhou et al. (2017) **EA+AV**: Thomas et al. (2015)
Empathy (caring)	How caring and empathic the user perceives reactions from the DHR to be	**EA**: Abdullah et al. (2018), Bickmore et al. (2005a), Bickmore et al. (2005b), Creed & Beale (2012), King et al. (2013), Lisetti et al. (2013), Zhou et al. (2017)
Enjoyment (entertainment)	How much the user enjoys the interaction with the DHR	**EA**: Bickmore et al. (2010), Klaassen (2013b), Lisetti et al. (2013) **AV**: Kim et al. (2014), Koulouris et al. (2020), Li & Lwin (2016), Navarro et al. (2020a) **EA+AV**: Peng (2009)
Friendliness (politeness)	How friendly the DHR appears to be	**EA**: Abdullah et al. (2018), Bickmore et al. (2005a), Bickmore et al. (2007)
Knowledgeability (competence, informativeness, intelligence)	How intelligent and competent the user perceives the DHR to be	**EA**: Abdullah et al. (2018), Bickmore et al. (2005a), Creed & Beale (2012), de Rosis et al. (2006), Lisetti et al. (2013), Olafsson et al. (2019, 2020), Schulman & Bickmore (2009)

Table 1. Psychological Constructs Evaluated in the 60 Papers in the Review

Likeability (appreciation, liking)	How much the user likes the DHR	**EA**: Bickmore et al. (2005a, 2005b), Creed & Beale (2012), de Rosis et al. (2006), Friederichs et al. (2014), Lisetti et al. (2013), Olafsson et al. (2019, 2020), Yasavur et al. (2014), Zhou et al. (2017)
Naturality (anthropomorphism, lifelikeness, realism, plausibility)	How realistic and life-like the user perceives the DHR to be	**EA**: Abdullah et al. (2018), de Rosis et al. (2006), Klaassen et al. (2013b), Lisetti et al. (2013), Olafsson et al. (2019, 2020), van Vugt et al. (2006)
Persuasiveness (relevance)	How convincing of a different opinion the DHR is	**EA**: de Rosis et al. (2006), Friederichs et al. (2014), Mazzotta et al. (2009), Oyibo et al. (2018), Schulman & Bickmore (2009), **AV**: Ahn et al. (2014b)
Repetitiveness (habitability)	How repetitive the interaction with the DHR is	**EA**: Bickmore et al. (2005a), Bickmore et al. (2010), Yasavur et al. (2014)
Satisfaction	How much the DHR fulfills the user's expectations	**EA**: Abdullah et al. (2018), Bickmore et al. (2013a, 2013b), Bickmore et al. (2005a), Gardiner et al. (2017), King et al. (2020), Murali et al. (2020), Olafsson et al. (2019, 2020), Watson et al. (2012), Zhou et al. (2017) **AV**: Andrade et al. (2016), Napolitano et al. (2013)
(Self-)presence (identification, representativeness)	How much the user feels correctly represented by the DHR	**EA**: Lisetti et al. (2013) **AV**: Ahn et al. (2014b), Behm-Morawitz et al. (2016), Fox et al. (2009), Kim et al. (2014), Koulouris et al. (2020), Li & Lwin (2016) Lyles et al. (2017), Navarro et al. (2020a), Song et al. (2013) **EA+AV**: Kim & Sundar (2012b)
Similarity (resemblance)	How similar the user perceives the DHR to be compared to himself	**EA**: Olafsson et al. (2019, 2020), van Vugt et al. (2006, 2009) **AV**: Fox & Bailenson (2009), Morie et al. (2013), Navarro, Cebolla, et al. (2020) Navarro, Peña, et al. (2020), Peña et al. (2016), Thompson et al. (2016), Waddell et al. (2015)
Social distance (personal relevance, relatedness, sociability)	How related on a personal level the user feels to be to the DHR	**EA**: Bickmore et al. (2005b), Friederichs et al. (2014), King et al. (2013), Lisetti et al. (2013), Murali et al. (2020), van Vugt et al. (2006, 2009), Zhou et al. (2017) **AV**: Ahn (2015), Ahn et al. (2014b)
Trustworthiness (ethics, honesty, sincerity, trust)	How much the user trusts the DHR and its messages	**EA**: Bickmore et al. (2005a, 2005b), Bickmore et al. (2010), Creed & Beale (2012), de Rosis et al. (2006), Friederichs et al. (2014), Lisetti et al. (2013), Olafsson et al. (2019, 2020), Schulman & Bickmore (2009), van Vugt et al. (2006, 2009), Zhou et al. (2017)
Usefulness (helpfulness)	How much utility and practical worth the DHR has for the user	**EA**: Abdullah et al. (2018), Bickmore et al. (2005b), Bickmore et al. (2013a), de Rosis et al. (2006), King et al. (2020), Lisetti et al. (2013) Mazzotta et al. (2009) **EA+AV**: Thomas et al. (2015)

Note: we list constructs alphabetically. We include only constructs that at least three reviewed papers mentioned. All constructs evaluated by the reviewed studies were self-reported by the user (usually based on Likert scales).
EA = embodied agent, AV = avatar, EA+AV = embodied agent and avatar(s).

4.2.1 Likeability and Friendliness

Overall, all employed embodied agents yielded high likeability levels. An agent's ability to show emotion and empathy constitutes a key design factor for likeability. Users generally perceived agents who showed emotions or modeled user emotions as likeable (Bickmore et al., 2005b; Creed & Beale, 2012; Lisetti et al., 2013). Lisetti et al. (2013) found a link between empathy and positive user perceptions. Agents can convey empathy using language cues and psychological capabilities (e.g., simulated emotion using gestures and facial expressions) that show they care for the users' situation. Caring for the users' situation goes hand-in-hand with understanding users' current feelings. Over the long run, empathy can affect the social bond between users and agent systems and, thus, also whether BCIs succeed (Bickmore et al., 2005b; Bickmore et al., 2010; Creed & Beale, 2012). Interaction friendliness connects to social bond and behavior change. In an experimental setting, Bickmore et al. (2007) showed that more friendly rather than impolite interruptions achieved higher success in changing behavior over the long run. Surprisingly, cultural adaptations to the user population (e.g., young Americans with Chinese background) neither increased perceived empathy nor likeability (Zhou et al., 2017). In contrast, Indian looks and argumentation targeted to an Indian audience resulted in higher satisfaction levels (Murali et al., 2020).

4.2.2 Trustworthiness and Credibility

Generally, users perceived agents as trustworthy and honest based on their psychological and language cues. Agents using empathic speech and non-verbal behavior yielded higher trustworthiness (Lisetti et al., 2013), subject to the study setup's complexity and the DHR's ability to recognize the users' emotions (e.g., using face recognition) (Creed & Beale, 2012; Friederichs et al., 2014). Concerning physical cues, van Vugt et al. (2006, 2009) found that, somewhat surprisingly, users perceived more obese agents as more trustworthy, possibly due to their higher similarity and lower social distance. In general, Lee and Choi (2017) established that trust and enjoyment facilitate increased user satisfaction and intention to use. Trust closely relates to credibility, especially for psychologically complex topics (e.g., adverse health consequences). For example, an agent's facial expressions need to match the situation to support credibility adequately (Creed & Beale, 2012). Similarly, Spence et al. (2013) found that emotionally correct content presentation, cultural factors, and stereotypes influence credibility.

4.2.3 Knowledgeability and Persuasiveness

Naturally, the information conveyed via the message content (de Rosis et al., 2006) and the interaction's structure (Bickmore et al., 2005; Lisetti et al., 2013) influence an agent's knowledgeability. Users perceived agents as intelligent, competent, and informative about the targeted BCI topic. Also, physical features were connected to knowledgeability. For example, users perceived a more obese agent as more knowledgeable about nutrition and physical activity, which aided in persuading them about health behaviors (van Vugt et al., 2009). Overall, DHRs exhibited higher persuasiveness than pure text-based interventions (Mazzotta et al., 2009)—mainly when they resembled users visually (Ahn et al., 2014b)—and exhibited relational behavior (Lisetti et al., 2013). Beginning a conversion with social talk can increase persuasiveness and knowledgeability (Olafsson et al., 2019; Schulman & Bickmore, 2009). Further, behavior modeling was more persuasive if designers adapted DHR gender to user gender (Oyibo et al., 2018). Lisetti et al. (2013) found a connection between knowledgeability and usefulness, which describes how users assess a DHR to enhance their everyday behavior and whether the provided messages help. Adding relational behavior significantly increased perceived usefulness (Bickmore et al., 2005b; Lisetti et al., 2013).

4.2.4 Presence

Research has identified the degree to which users felt as though the DHR was present in the same environment as a critical construct for behavioral outcomes (Johnston et al., 2012). For instance, a higher presence was associated with increased physical activity and healthy eating (Behm-Morawitz, 2013). In our review, self-avatar studies in particular tested presence and showed that virtual faces similar to a user's actual face (Song et al., 2013), customization (Kim & Sundar, 2012b), and adapting avatar physical appearance to virtual world behavior (Fox et al., 2009) increased presence and identification with the avatar[3]. Similarly, the level of "interface embodiment" (i.e., the degree to which the avatar followed real-world user movements, e.g., based on camera input) positively influenced presence, enjoyment, and participation in the BCI (Kim et al., 2014). High-presence male users copied their avatars' eating behavior in consuming more cookies, while high-presence female users reduced their cookie consumption compared to their low-presence female peers (Fox et al., 2009). Finally, studies found that presence drives perceived personal relevance of communicated messages (Ahn, Fox, et al., 2014) and increases enjoyment and intention to use (Kim et al., 2014; Li & Lwin, 2016).

4.2.5 Similarity and Attractiveness

Designers can achieve visual similarity to users by adapting a DHR's physical design elements. They can achieve behavioral similarity by adapting behaviors according to the target group's culture (Zhou et al., 2017) or imitating user expressions (Lisetti et al., 2013), a common strategy in health communication (Spence et al., 2013). Other means to increase similarity include adapting the DHR's physical appearance

[3] In their embodied agent study, Lisetti et al. (2013) evaluated "social presence". However, they operationalized the construct in a way closely related to the concept of naturality.

to users' size (van Vugt et al., 2006, 2009), appearance (Thompson et al., 2016), and gender (Waddell et al., 2015) and showing the desired target behavior (Fox & Bailenson, 2009). Similarity decreased the social distance between users and DHRs (van Vugt et al., 2006, 2009). It drove attractiveness (Pratt et al., 2007), which was associated with higher perceived intelligence, trustworthiness, persuasiveness, and likeability (Creed & Beale, 2012). Physical cues mainly determined attractiveness. For avatars, a more attractive self-avatar goes hand-in-hand with changing the social role from actual-self to ideal-self, which positively influenced behavioral outcomes (Jin, 2009; Kim & Sundar, 2012b). Other factors include lifelike shapes and colors adapted to user preferences.

4.2.6 Naturality and Social Distance

Naturality describes the degree to which users perceive a DHR as realistic and humanlike. Researchers evaluated naturality, in particular with embodied agents, and found it highly connected to physical cues (Lisetti et al., 2013). Naturality also relates to language and psychological cues. For example, while a DHR's skin color and texture should be realistic, designers should also adapt utterances to individual users (Fox et al., 2009; Friederichs et al., 2014). Naturality influenced the feeling of presence (Kim et al., 2014) and, thus, also impacted intervention uptake. More realistic DHRs, similar to the user, reduced the perceived social distance (i.e., the feeling of social relatedness to the DHR) and facilitated behavior change (Ahn, 2015; van Vugt et al., 2006, 2009). Further, facial expressions, social chat, and gesture use can simultaneously decrease social distance and increase the agent's relatableness and sociability (Bickmore et al., 2005b; Lisetti et al., 2013).

4.2.7 Enjoyment

Researchers have evaluated various types of social design features for enjoyment. With respect to the narrative point of view, users preferred first-person stories from an agent over stories from a third-person perspective (Bickmore et al., 2010). They perceived a low speaking speed as little enjoyable, which was connected to low intentions to use (Klaassen et al., 2013b). For psychological and physical cues, an agent showing empathy with gestures increased the perceived enjoyment compared to a non-empathic agent or a pure text-based interaction, both of which users perceived as similarly little enjoyable (Lisetti et al., 2013). Studies found a strong connection between enjoyment and both behavioral intentions and effective behavior change in digital and classic face-to-face interventions (Bickmore et al., 2010; Schneider & Cooper, 2011). Further, they found that repetitiveness in agent clothing, behavior, and messages harms the enjoyment and, thus, that designers should avoid it (Bickmore et al., 2010).

4.2.8 Ease of Use and Satisfaction

To gain first impressions towards long-term use, system designers often evaluate users' perceived ease of use and satisfaction after they have used a system for a certain period. Overall, studies reported ease of use and user satisfaction with DHR-based interventions to be at least as high as for comparable paper-based interventions (e.g., Gardiner et al., 2017; Olafsson et al., 2019). Ease of use and satisfaction play a crucial role in system acceptance and highly depend on other constructs such as trustworthiness and repetitiveness (Bickmore et al., 2010; Kassim et al., 2012). Further, ease of use and satisfaction with a system drive usage intentions, a direct proxy for the actual DHR use and, thus, BCI uptake (Bickmore et al., 2010; Lehto et al., 2012).

Looking at the results in this subsection more broadly, we identified no single psychological construct that stands alone. The multitude of constructs available affects how users psychologically evaluate DHRs. Hence, multiple social cues in a DHR in combination cause the impact that DHR design has on user perception and cognitive evaluation. In particular, contradictions among different types of social cues (e.g., a mismatch between appearance and argumentation) may harm perception (Murali et al., 2020). An intervention's content and the psychological constructs related to the DHR delivering the BCI may support each other in helping users adopt BCIs. Hence, in Section 4.3, we look at the different intervention types that the papers in our sample used.

4.3 Results on Behavior Change Intervention Functions

The identified constructs relate to and depend on one another, which renders the way in which users perceive DHRs a multifaceted experience. In addition to a DHR's social design, user psychology and behavior are also subject to pre-intervention behavior and the provided intervention content. Depending on the application and context, different psychological constructs may support the BCI. Yet, by diving into the most used BCIs and psychological constructs, we focus on removing some of this ambiguity.

In particular, research has shown that having a relational or empathic counselor as compared to a non-relational one positively impacted the persuasion intervention function (Bickmore et al., 2005a, 2005b; Lisetti et al., 2013; Yasavur et al., 2014). As per the COM-B model, increased persuasion leads to a direct increase in motivation with other possible impacts on behavior, capability, and opportunity via interactions among the different functions. The above sources from our sample (Bickmore, Caruso, et al., 2005; Bickmore, Gruber, et al., 2005; Lisetti et al., 2013; Yasavur et al., 2014) also confirmed as much. In addition, using a humorous agent may lead to increased motivation compared to a non-humorous agent (Olafsson et al., 2019, 2020; Schulman & Bickmore, 2009). To improve the rate at which users take up educational content and persuasion interventions, research has increased perceived trust and credibility by including a graphically more appealing agent and social dialog (Olafsson et al., 2019; Schulman & Bickmore, 2009), or by increasing the agent's physical similarity to users (van Vugt et al., 2006, 2009). Unsurprisingly, research has shown that a high satisfaction with a DHR positively influenced users' motivation and desire to continue the intervention (i.e., especially emphasizing the persuasion intervention function) (Bickmore et al., 2013b; Watson et al., 2012).

In contrast, cultural adaptation has attracted a much more controversial discourse: while associated stereotypes corresponding to an anticipated user group's physical features may also negatively affect users' motivation to change the behavior that a DHR ideally addresses, research has reported a positive effect when adapting the way in which a DHR employs argumentation. This enables users to understand the conveyed message more easily; that is, it improves users' psychological capability in the COM-B model (Murali et al., 2020; Zhou et al., 2017). To cluster the employed BCIs, we link each study to at least one of the nine intervention functions provided by the COM-B model (Michie et al., 2011). Most studies (81.7%) used multiple intervention functions; in particular, 17 papers used two, 21 papers used three, and 11 papers used four or more intervention functions. Eleven papers used only one intervention function. As the most widely employed combination of intervention functions, studies employed education, persuasion, and enablement.

Table 2 summarizes the used intervention functions grouped by the targeted COM-B components (capability, motivation, and opportunity) that Noorbergen et al. (2019) provided. We can see that interventions using avatars mainly targeted motivation (by using the intervention functions coercion, incentivization, modeling, and persuasion) and physical capability (via training interventions). In contrast, embodied agents targeted all COM-B components. The corresponding psychological constructs that avatar studies mainly tested included presence, similarity, social distance, and (seldomly) enjoyment. Agent studies mostly used the intervention functions education, persuasion, and enablement, referring to empathy, knowledgeability, likeability, social distance, and trustworthiness in the evaluation. For training and coercion intervention functions, we identified a comparably small number of papers that investigated psychological constructs.

4.3.1 Capability

Education and training interventions aim to increase users' physical and psychological capabilities (Michie et al., 2011; Noorbergen et al., 2019). We classified 28 studies (46.7%) as education interventions, that is, as increasing knowledge or understanding (Michie et al., 2014). Studies primarily used agents for this intervention function, such as to provide information about healthy food options. Furthermore, 16 studies (26.7%) used training interventions (seven agent studies, six avatar studies, and three avatar-agent combined studies). The avatar-agent combinations used virtual worlds to practice behavior in certain situations, such as social eating at parties (Thomas et al., 2015), to impart psychological skills.

4.3.2 Motivation

The intervention functions persuasion, modeling, coercion, and incentivization mainly focus on increasing users' reflective and automatic motivation (Michie et al., 2011; Noorbergen et al., 2019). Most papers in our review (42 of 60 papers / 70%) employed persuasion interventions by trying to induce positive or negative feelings in users and, thereby, persuade them to behave in a healthier way. We found that 22 (36.7%) papers used modeling, which refers to providing an example to aspire to or imitate (Michie et al., 2011). Of these 22 papers, 18 used avatars, one used an embodied agent (Oyibo et al., 2018), and three used avatars and embodied agents to model behavior. Thus, we see a strong tendency towards tailoring modeling interventions by using personalized avatars. Similarly, we found that the five studies (8.3%) that used coercion interventions, which involve creating an “expectation of punishment or cost” (Michie et al., 2011, p. 7) all used avatars. We classified only four papers (6.7%) as using incentivization functions, which refers to creating an expectation of a reward. However, one could argue that many studies we classified as modeling interventions could also be seen as incentivization interventions if the user accepted the image of their future-self as an incentive.

Table 2. Intervention Functions and Relationship to Psychological Constructs

Construct	Capability		Motivation				Opportunity	
	EDU (28)	TRA (16)	PERS (42)	MOD (22)	COE (5)	INC (4)	ENAB (33)	ENVR (6)
Satisfaction	11 | 1 | -	3| - | -	10| 2 | -	- | 1 | -		2 | - | -	11 | - | -	2 | - | -
Trustworthiness	11 | - | -		11 | - | -			1 | - | -	10 | - | -	3 | - | -
Ease of use	7 | - | 1	- | - | 1	8 | - | 1			2 | - | -	7 | - | 1	3 | - | -
Likeability	8 | - | -		10 | - | -			1 | - | -	8 | - | -	3 | - | -
Knowledgeability	7 | - | -		8 | - | -			2 | - | -	6 | - | -	4 | - | -
Usefulness	5 | - | 1	1| - | 1	8 | - | 1			1 | - | -	6 | - | 1	2 | - | -
Empathy	7 | - | -		7 | - | -			2 | - | -	6 | - | -	4 | - | -
(Self-)Presence	1 | - | 1	- | 3 | -	1 | 3 | 1	- | 7 | 1	- | 2 | -	- | 1 | -	1 | 2 | -	1 | - | -
Social distance	7 | - | -		6 | - | -	- | 2 | 1	- | 2 | -		6 | - | -	1 | - | -
Similarity	4 | - | -	- | 1 | -	2 | 3 | -	- | 6 | -	- | 1 | -	- | 1 | -	2 | 3 | -	
Enjoyment	2 | - | 1	- | 3 | 1	3 | 1 | -	- | 2 | 1		- | 1 | -	3 | 1 | -	1 | - | -
Naturality	5 | - | -		6 | - | -			1 | - | -	5 | - | -	2 | - | -
Credibility	3 | - | 2	- | - | 2	3 | - | 1	- | - | 1			2 | - | 1	
Friendliness	3 | - | -		3 | - | -			1 | - | -	2 | - | -	3 | - | -
Persuasiveness	1 | - | -	1 | - | -	4 | - | -	1 | 1 | -	- | 1 | -		3 | - | -	
Repetitiveness	3 | - | -		3 | - | -			1 | - | -	3 | - | -	1 | - | -
Attractiveness	1 | - | 1		1 | 1 | 1	- | - | 1			1 | - | -	

Note: we list constructs by decreasing number of occurrences. Numbers represent how often studies investigated a construct-intervention combination for different DHRs: # embodied agent studies | # avatar studies | # studies that used both avatars and embodied agents. Blank fields mean that no study investigated the combination. We show totals in parentheses. Single papers may investigate multiple psychological constructs and affect the numbers in multiple rows and columns. EDU = education, TRA = training, PERS = persuasion, MOD = modeling, COE = coercion, INC = incentivization, ENAB = enablement, ENVR = environmental restructuring. No study used the intervention function “restriction”; hence, we omit it from the table.

4.3.3 Opportunity

Enablement, environmental restructuring, and restriction functions attempt to alter users’ opportunities (Michie et al., 2011). We found that 33 papers (55%) used enablement interventions (i.e., they increased means or reduced barriers to increase the user's opportunity). We assigned primarily embodied agent studies to this category. Embodied agents enable users to have personal and professional communication about behavior change that reduces mental barriers. Further, six papers (10%) used environmental restructuring interventions that change aspects of a user’s physical and/or social environment. No study used restriction interventions (i.e., setting rules to reduce the opportunity to engage in the target behavior). Instead, various studies provided educational content on self-restricting unwanted behavior or supporting self-restriction, such as setting a quit smoking date (Abdullah et al., 2018).

4.4 Results on Health Behavior Change

4.4.1 Targeted Health Behavior

The majority of studies targeted physical activity (29 studies / 48.3%) followed by nutrition (8 studies / 13.3%), smoking (3 studies / 5%), and alcohol overconsumption (2 studies / 3.3%). Further, 15 studies (25%) simultaneously targeted nutrition and physical activity, one study (1.7%) targeted alcohol and nutrition (Fuchs et al., 2019), and two studies (3.3%) focused on all four SNAP behaviors. However, some evidence shows that targeting multiple behaviors simultaneously may be disadvantageous: Bickmore et al. (2013) found that their agent effectively targeted either nutrition or physical activity. However, a combined intervention targeting both behaviors saw reduced success for physical activity.

4.4.2 Measuring Changes in Health Behavior

Based on Palvia et al.'s (2015) categories, we classify the methods that the studies in our review employed to evaluate the DHRs' fidelity and measure changes in health behavior (see Table 3). Most studies used laboratory experiments (36 studies / 60%) followed by field research (23 studies / 38.3%) and surveys (7 studies / 11.7%). Note that four papers (6.7%) reported more than one method.

Table 3. Targeted SNAP health behaviors, methods, and measures

Behavior	Method: measure
Physical inactivity	**Lab: activity sensors / step count** (Joo & Kim, 2017; Koulouris et al., 2020; Maher et al., 2020; Navarro et al., 2020b; Peña et al., 2016; Peña & Kim, 2014), **confidence / commitment to change** (Thomas et al., 2015), **coupon choice** (Kim & Sundar, 2012b; Waddell et al., 2015), **heart rate** (Kim et al., 2014; Navarro, Peña, et al., 2020), **instant rest time** (Bickmore et al., 2007), **intention to use** (Bickmore et al., 2007; Olafsson et al., 2020; Zhou et al., 2017), **intention to change** (Kim et al., 2014; Li et al., 2014; Li & Lwin, 2016; Waddell et al., 2015), **psychological constructs only** (Schulman & Bickmore, 2009; Thompson et al., 2016), **self-efficacy** (Murali et al., 2020; Peng, 2009), **self-reported activity** (Fox & Bailenson, 2009) **Field: intention to use** (Bickmore et al., 2005a, 2005b; Bickmore et al., 2013a; Bickmore et al., 2010; Gardiner et al., 2017; King et al., 2013), **pedometer** (Bickmore et al., 2013a, 2013b; Bickmore et al., 2005a, 2005b; Bickmore et al., 2010; King et al., 2020, 2013; Watson et al., 2012), **psychological constructs only** (Klaassen et al., 2013a, 2013b), **self-efficacy / confidence** (Behm-Morawitz et al., 2016; Gardiner et al., 2017; Napolitano et al., 2013), **self-report** (Behm-Morawitz et al., 2016; Friederichs et al., 2014, 2015; Gardiner et al., 2017; King et al., 2020; Maher et al., 2020; Mohan et al., 2020; Navarro et al., 2020a; Vainio et al., 2014), **weight loss** (Johnston et al., 2012; Napolitano et al., 2013), **vital parameters** (vitality score, heart rate, blood pressure, BMI) (King et al., 2020) **Survey: intention to use** (van Vugt et al., 2006, 2009), **motivation / intention to change** (Schmeil & Suggs, 2014), **self-report** (Morie et al., 2013), **self-efficacy, self-regulation, outcome expectations** (Oyibo et al., 2018)
Nutrition	**Lab: confidence / commitment to change** (Thomas et al., 2015), **coupon choice** (Kim & Sundar, 2012b), **instant food choice** (Fox et al., 2009; Joo & Kim, 2017; Sah et al., 2017), **intention to use** (Olafsson et al., 2020), **psychological constructs only** (de Rosis et al., 2006; Jin, 2009; Mazzotta et al., 2009), **risk perception** (Ahn et al., 2014b), **self-efficacy** (Olafsson et al., 2019; Peng, 2009), **self-report** (Ahn, 2015) **Field: intention to use** (Bickmore et al., 2013a; Gardiner et al., 2017), **self-efficacy / confidence** (Behm-Morawitz et al., 2016; Gardiner et al., 2017; Napolitano et al., 2013), **self-report** (Behm-Morawitz et al., 2016; Bickmore et al., 2013a; Fuchs et al., 2019; Gardiner et al., 2017; Maher et al., 2020; Vainio et al., 2014), **weight loss** (Johnston et al., 2012; Napolitano et al., 2013) **Survey: intention to use** (van Vugt et al., 2006, 2009), **motivation / intention to change** (Schmeil & Suggs, 2014), **psychological constructs only** (Creed & Beale, 2012)
Smoking	**Lab: coupon choice** (Kim & Sundar, 2012b), **intention to use** (Song et al., 2013), **intention / motivation to quit** (Abdullah et al., 2018; Andrade et al., 2016) **Field: intention to use, self-efficacy / confidence, self-report** (Gardiner et al., 2017)
Alcohol overcon-sumption	**Lab: coupon choice** (Kim & Sundar, 2012b), **intention to use** (Lisetti et al., 2013; Yasavur et al., 2014) **Field: intention to use, self-efficacy / confidence** (Gardiner et al., 2017), **self-report** (Fuchs et al., 2019; Gardiner et al., 2017)

We may explain the fact that so many studies used laboratory experiments (range: 15 to 322 participants, median: 61) based on 1) the notion that some experiment setups require dedicated hardware that researchers could not provide to users for a prolonged period and 2) the higher control level in laboratory environments. Field studies (range: 6 to 4,302 participants, median: 54) provide a longer observation period and, thus, make it possible to observe changes in different COM-B model components and physical outcomes over longer periods. The duration varied from one week to one year. In particular, long-term studies reported high attrition rates over time. For example, Friederichs et al. (2015) reported an overall attrition rate of approximately 65 percent for a year. Surveys (range: 50 to 673 participants, median: 259) commonly employed interactive online questionnaires where users first had some time to interact with the

DHR and answered a questionnaire afterward. The interaction with the DHR took from one to six minutes on average though some papers did not provide details.

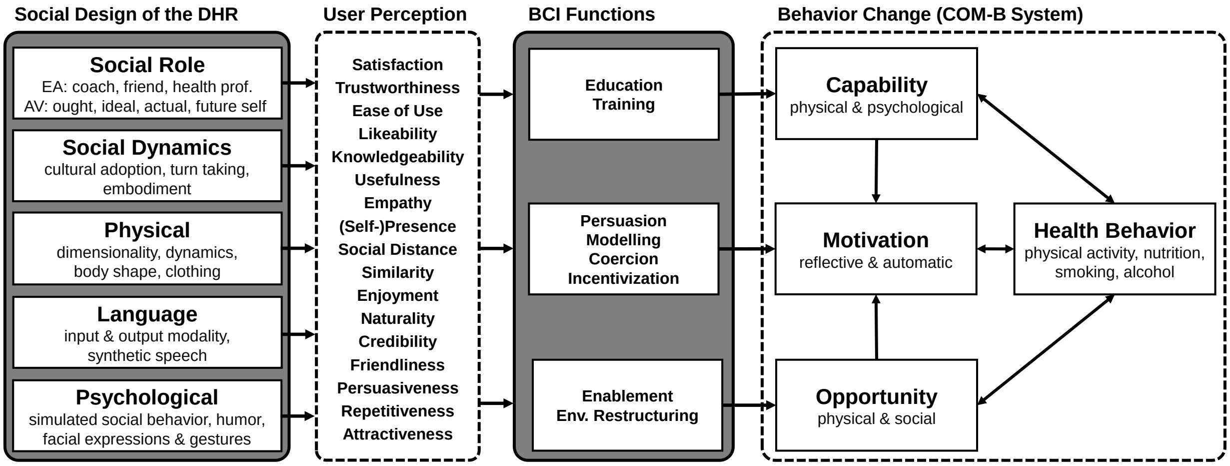
The most widely employed outcome measure across all study types was intention to use (17 studies, 28.3%), which generally yielded high levels. This measure assumes that users can realistically project how they will use DHR for behavior change in the future. In laboratory experiments, behavioral measures often included step count/activity measures during the experiment (Joo & Kim, 2017; Peña et al., 2016) and instant food/coupon choices after the experiment (e.g., Kim & Sundar, 2012b; Waddell et al., 2015). Evaluations in field studies included self-reports (i.e., alcohol/cigarette consumption, food intake, and physical activity), user weight throughout the BCI, and pedometer data as quantification of physical activity. For smoking, studies also used a quit date as a behavioral measure (Abdullah et al., 2018). In online surveys, measures for health behavior included users' self-reported feelings towards behavior, such as the motivation to change the targeted behavior (Creed & Beale, 2012), or outcome expectancies when continuing the DHR-based intervention (e.g., Oyibo et al., 2018).

4.4.3 Effectiveness of Interventions to Change Health Behavior

Overall, many studies we reviewed showed that one can effectively use DHRs for SNAP behavior change. The studies confirmed that a DHR's social design influences user perceptions and impacts an intervention's success. Compared to control groups that did not use a DHR-based intervention or used another type of intervention such as information sheets (e.g., Bickmore et al., 2005a; Gardiner et al., 2017), DHR-based intervention users reported higher fruit and vegetable consumption (Bickmore, Schulman, et al., 2013; Gardiner et al., 2017), decreased self-reported food consumption (Ahn, 2015), increased physical activity (Bickmore, Silliman, et al., 2013; Bickmore, Caruso, et al., 2005; Bickmore et al., 2005b; Bickmore et al., 2013a; Bickmore et al., 2010; Friederichs et al., 2014, 2015; King et al., 2013; Watson et al., 2012), increased exercise efficacy (Ahn, Fox, et al., 2014), and reduced alcohol consumption (Gardiner et al., 2017). Only a few studies reported that DHRs had an insignificant impact on intervention outcome compared to a control group (Andrade et al., 2016; Fuchs et al., 2019; Klaassen et al., 2013b). In contrast, other studies found DHRs as effective as other BCI deliveries such as human advisors (Johnston et al., 2012; King et al., 2020) and superior to information sheets (Gardiner et al., 2017). DHRs significantly altered participants' behavior in comparison to control groups (Bickmore et al., 2013b; Watson et al., 2012) or pre-study behavior (Maher et al., 2020; Mohan et al., 2020).

DHR interventions increased confidence and motivation for physical activity and nutrition (Olafsson et al., 2019; Thomas et al., 2015). Studies reported significant differences between pre- and post-intervention user weight for avatar-based interventions targeting physical activity and nutrition (Johnston et al., 2012; Napolitano et al., 2013). Studies that compared different DHR designs and DHR behavior variations reported significant differences in behavioral intentions and observed behaviors between the conditions tested (e.g., Bickmore et al., 2007; Joo & Kim, 2017; Morie et al., 2013; Sah et al., 2017; van Vugt et al., 2006). Especially, studies reported significant differences when comparing agent-based to text-only interventions (e.g., Schulman & Bickmore, 2009) and empathic to non-empathic agents (e.g., Bickmore, Caruso, et al., 2005; Lisetti et al., 2013).

Overall, our results show that research has implemented different BCI types using DHRs facilitated through a range of social design features (Fogg, 2003). Thereby, we can see that, depending on the DHR design, the interaction triggers various positive or negative user perceptions. For example, empathic behavior in DHRs leads to higher likeability, trustworthiness, and enjoyment during interactions with them (Lisetti et al., 2013). The triggered psychological constructs influence BCI functions' applicability and effectiveness. Likeability, trustworthiness, and enjoyment positively influence persuasion during an intervention (Bickmore et al., 2005b; Bickmore et al., 2010; Creed & Beale, 2012) to motivate users to behave in a certain way. BCI functions influence the sources of human behavior (capability, motivation, opportunity) and, thereby, help individuals achieve changes in behavior (Michie et al., 2011). The results demonstrate that how one designs a DHR can have a significant impact on behavior change via the user perception constructs triggered and the BCI functions selected. Therefore, when selecting appropriate BCI features during the design phase, designers need to consider already which constructs might be beneficial or harmful in the intervention and which design features they should use accordingly. Figure 4 summarizes our findings.



Notes: we show typical social design features and behavior change elements from the literature corpus. We list user perception constructs by decreasing number of occurrences. We group BCI functions by behavior change component primarily targeted; in each of three groups, we list BCI functions by decreasing number of occurrences. We do not show functions not included in the literature corpus. EA = embodied agent, AV = avatar.

Figure 4. Overview of the Results

5 Discussion

5.1 Summary of Findings and Interplay of Components

Over the last 15 years, researchers have created and evaluated DHR designs to facilitate technology-mediated interventions for health behavior change in the SNAP domain. Variations in the DHR's social design have yielded important differences in user perceptions that affected the interventions' efficiency in targeting users' capability, opportunity, motivation, and behavior. In this paper, we conducted a structured literature review to establish the current body of knowledge for the role that DHR design plays in behavior change in the SNAP domain. We summarize the key relationships between DHR design, user perceptions, and intervention functions in a structured manner to facilitate behavior change (see Figure 4).

Given the myriad foci in the individual studies (e.g., physical activity, nutrition) along with the different methods (e.g., lab, field), measures (e.g., various constructs, outcome variables), and alternative BCI delivery modes (e.g., text-based, no intervention), we could not exhaustively evaluate all possible cause-and-effect relationships that the arrows indicate in the overview in Figure 4. Many possible interrelations between DHR design and user perception and between user perception and BCI interventions exist, and the extant literature has not studied all potential interrelations. Thus, we do not find it sensible to show the exact matching of design, perception, and BCI functions. Hence, this paper aimed to summarize the different types of social cues, psychological constructs, BCI functions, and outcome variables in the SNAP health behavior change context. We conducted a risk of bias analysis of the underlying study designs (see Appendix B).

Based on the insights from our literature corpus and on existing frameworks, we conclude that design features (based on DHRs' social cues) cause psychological reactions from users that can support the BCI functions and behavior change. We point out initial evidence for such effects in Section 4.3, while we emphasize context dependency of any given effect relating to DHR design, BCI, behavior change goal, and participant population. In Section 4, we highlight the constructs and interrelations typically studied in extant literature. Studies mainly explored improving capabilities via the effect that DHR design has on satisfaction, trustworthiness, and likeability in delivering education interventions. Studies examined these three user perceptions—satisfaction, trustworthiness, and likeability—the most regarding their effect on persuasion to increase motivation and enablement to improve opportunities. Since the studies we examined used heterogeneous designs and measures, we could not provide a numerical meta-analysis; yet, theoretical reasoning and the cumulative empirical evidence suggest that designing embodied agents in a way that caters to these user perceptions tends to impact SNAP-related behavior positively. We lack respective evidence regarding avatars. For avatar design, studies focused particularly on the effect that (self-)presence and similarity perceptions have on modeling, persuasion, and enablement. Like before with other mechanisms for agents, theoretical reasoning and the cumulative empirical evidence suggest positive effects on behavior change. Researchers should take these findings as a starting point for understanding what has been effective so far in many studies. However, it should not limit future research on these mechanisms. The DHR's social design relates to a range of primary social cue types (Fogg, 2003). So far, interventions in this area have primarily relied on self-avatars and agents and rarely examined the interplay between self-avatars and other-avatars. Self-avatars employed a range of self-concepts, such as actual-, ideal-, ought-, and future-self, whereas embodied agents acted as counselors, friends, health professionals, and behavior change opponents. Similar to the real world, the social dynamics of these interactions are vital (e.g., cultural adaptation and turn-taking).

Further, physical cues such as a DHR's body shape, clothing, dimensionality, dynamics, and photorealism affect users' perceptions of similarity, a critical construct for intervention outcomes. Researchers relied on synthetic speech, pre-recorded output, and written text for language cues. They mostly restricted user input to choosing an answer from a list with seldom free text input (e.g., as via Wizard-of-Oz studies) (Yasavur et al., 2014). In terms of psychological cues, researchers relied on humor, non-verbal behavior, and social chat that match the conversation content (e.g., gestures and facial expressions).

In our review, we identified the constructs most widely associated with DHR-based interventions. Avatar studies mainly evaluated presence and similarity. Agent studies also considered other constructs, such as attractiveness, credibility, knowledgeability, likeability, naturality, and trustworthiness. These user perceptions influence users' intervention uptake and effectiveness through a range of psychological mechanisms. The user perceptions that a DHR's social design triggers support and/or hinder BCI functions. For instance, knowledgeability and trustworthiness facilitate education and persuasion interventions, while presence drives modeling interventions. Likely, the increased physical similarity between DHR and user and an empathic agent support the persuasion intervention function. At the same time, cultural adaptation is a controversial topic, as its effects also depend on stereotypes that designers may not consider or anticipate at the time of system design. Overall, agent studies mainly relied on education, persuasion, and enablement, while avatar studies mainly employed intervention functions targeting motivation (i.e., coercion, incentivization, modeling, and persuasion) or physical capability (i.e., training).

Taken as a whole, the majority of the reviewed studies provided empirical support that one can successfully use DHRs for BCIs, especially compared to pure text-based interventions (see Section 4.4.3). Nonetheless, readers should not understand this review as definitive advice to use DHRs for SNAP behavior change. Each time someone applies DHRs, one needs to carefully consider the unique circumstances that surround the targeted health behavior, the intervention's audience, and the possible alternatives to DHRs for delivering BCIs. Individual studies found that, for specific applications, DHRs can be similarly effective for delivering BCIs when compared to human advisors (Johnston et al., 2012; King et al., 2020) or superior to information sheets (Gardiner et al., 2017). Studies have also shown them to alter study participants' step counts significantly in comparison to non-intervention control groups (Bickmore et al., 2013b; Watson et al., 2012) or self-reported behavior in contrast to pre-study behavior (Maher et al., 2020; Mohan et al., 2020). Yet, the literature currently has neither systematically assessed the implications of the social relationship (e.g., empathy, caring) developed between user and DHR as part of the intervention nor compared the success of DHR-based BCIs to alternative delivery modes (e.g., text-based, dialogue). In particular, a comparison with the related field of human-robot interaction could benefit both fields. Robots have also become increasingly important in healthcare (Esterwood & Robert, 2020) to both treat people (Olaronke et al., 2017) and deliver health interventions (Kidd & Breazeal, 2008). In these cases, the social design elements influence the intervention's effectiveness. Despite different interaction modes, DHRs on a screen versus embodied physical robots, some findings we identified would also be useful for robot design (Esterwood & Robert, 2020; Olaronke et al., 2017; Złotowski et al., 2015). In particular, designers should consider the relationship between social design elements, psychological constructs, and behavior change that we have elaborated on when designing human-robot interactions. Therefore, researchers should consider which constructs support the desired outcome and which social design elements would suitably promote these constructs.

5.2 Practical Implications

Based on our review, we identified various factors that system designers should consider when using DHRs for behavior change in the SNAP domain.

First, system designers need to put the targeted health behavior at the forefront of all design considerations. The DHR's social design then follows on to achieve this end. Thus, building on the structure in Figure 4, designers need to approach the subject matter "from right to left". They can do so via specifying the targeted health behavior, user group, and COM-B components (capability, opportunity, and motivation) early on. For instance, focusing on one specific health behavior rather than multiple health behaviors yields better intervention outcomes (Bickmore et al., 2013a). Accordingly, designers should choose the intervention function(s) and then prioritize the psychological constructs that support these intervention functions (Michie et al., 2014). A DHR's design should reflect these decisions to ensure the best possible intervention uptake and, finally, success in behavioral terms. Our study provides support by showing which constructs and interrelations prior work has studied as well as references to the original papers to engage with detailed knowledge regarding focal constructs and interrelations.

Second, system designers need to carefully consider the type of social relationship they intend to build between users and DHRs as it has the power to impact the intervention uptake significantly. DHRs need to build a social relationship with users and convey empathy for users to comply with an intervention over the long run. Thus, designers should design DHRs to explicitly use verbal elements (e.g., voice pitch, tone, and specific speech content) and non-verbal elements (e.g., gestures and facial expressions) that resemble human communication. This consideration of verbal and non-verbal elements in DHR design goes hand in hand with rendering the intervention as more enjoyable, the DHR as more trustworthy, and information as more credible. A promising avenue in this regard is the co-design approach as it involves end users and other stakeholders early on and in all stages of the systems design and evaluation process (Noorbergen et al., 2021).

Third, system designers need to focus on maximizing the extent to which users perceive presence and similarity to the DHR. Conveyed through physical, social dynamics, and psychological cues, presence and similarity increase an intervention's perceived relevance (Yee & Bailenson, 2007) and, thus, also contribute to short-term compliance and long-term adherence. For example, avatars in interventions fostering physical activity should be shown as physically active. Also, designers can use different self-concepts to influence users' immanent self-perceptions and use them for the intervention. To enhance an avatar's similarity and attractiveness to the user, designers can implement customization to help users to bond with it and show an actual, ideal, ought, or future version of themselves.

Fourth, system designers need to carefully consider how they match intervention functions to a DHR's social design. For instance, studies building on embodied agents have primarily used education, persuasion, and enablement as intervention functions with support from the constructs, trustworthiness, satisfaction, and likeability. In contrast, studies building on avatars have so far primarily used coercion, incentivization, modeling, persuasion, and training to alter the user's motivation and physical capability. Studies have primarily used the user perception constructs (self-)presence, similarity, and enjoyment with these BCI functions, which demonstrates the need to match social design cues and psychological constructs according to the intended user perceptions that designers want to use to support the BCIs. Past research has shown that having a relational or empathic counselor as compared to a non-relational one can positively impact the intervention function of persuasion, which—according to the COM-B-model—leads to a direct increase in motivation with other possible impacts on behavior, capability, and opportunity for interactions among the different functions. Also, physical similarity plays an essential role in increasing trustworthiness and credibility, which researchers have successfully used to improve the uptake of education BCIs.

5.3 Knowledge Gaps and Directions for Future Research

Building on our review findings, we identify seven directions for future research. First, researchers need to better understand non-professional social roles for other-avatars and embodied agents. Up to now, most agents have acted as counselors or coaches, while the BCI literature suggests that non-professional roles can also support successful behavior change. This should also include the integration and contrasting of multiple roles. For example, one could combine a professional coach using an other-avatar for interpersonal communication once a week with an agent acting as an emotionally supportive friend daily. To this end, op den Akker et al. (2018) proposed the concept of a council of coaches for future research.

Further factors for future work include DHR age, gender, and gamification, which researchers have not yet systematically studied with SNAP BCIs. While many DHRs have focused on an educational and conversational approach towards communicating messages rather than for gamification, researchers have increasingly acknowledged avatars and agents as a tool for gamification. A body of research on gamification (with and without DHRs) to support health behavior change exists (e.g., Schmidt-Kraepelin et al., 2020). We see value in future research integrating DHR and gamification research to support health behavior change, especially regarding longer-term interventions where DHRs and gamification in a combined manner focus on resolving the attrition problem that some studies in our sample reported. Gamification could, for example, support interaction with a DHR over prolonged periods required for behavior change. Conversely, DHRs could support gamification, such as being the medium for communicating feedback, stimulating competition, or increasing the emotions related to receiving badges. Besides the social role, research has neglected the influence of social dynamics during BCIs. Such social dynamics include the interpersonal distance, initiation, timing, and interaction frequency with a DHR. Even though no paper in our review studied them, it is conceivable that users may perceive a lower interpersonal distance and feel socially closer when they can see only a DHR's face or upper body as compared to a full body image.

Second, more research needs to examine the user-DHR relationship's temporal dynamics. Similar to real-world relationships, social dynamics and perceptions may change over time. As such, system designers may consider changing a DHR's social design over time, which may decrease repetitiveness, a key reason for attrition (Bickmore et al., 2010). Changing social design over time also implies the need to understand the psychological constructs in a more detailed way, which researchers can achieve by more consequently modeling user feelings. Especially, an increased use of user feedback and sensors, such as activity trackers and video cameras, may support an improved modeling of user feelings (Rouast et al., 2021). Using this additional knowledge would allow researchers to adapt a DHR according to users' preferences and perceptions and, thus, increase their interest and motivation to participate in an intervention. To this end, comparisons about the influence that different social cues have on users in different populations could further help them tailor BCIs to specific user groups, or even single users, and their current feelings.

Third, based on established literature and findings from our literature corpus, we established that how users perceive DHRs affects whether they adopt BCIs in that different psychological constructs benefit certain intervention functions. However, while we have initial evidence, broader studies and the design of behavior change applications according to the findings from our framework remain an open point for future work. We have seen a plethora of constructs, especially regarding user perception. So far, the literature does not identify clear patterns about which design features have the most importance for user perceptions, and which perceptions best support specific BCIs, and, ultimately, behavior change. We do not see a strong need to extend the list of DHR design features or user perceptions. Instead, future research should systematically explore and report the relative extent to which design features and perceptions contribute to a systematic body of design knowledge.

Fourth, we need more research on coercion and restriction interventions. As most DHR-based interventions currently focus on positive emotions, we lack research on why users adopt or do not adopt interventions that use negative emotions. For instance, we do not know whether DHRs that additionally and/or exclusively build on coercion and restriction may facilitate positive behavioral change in alcohol overconsumption and smoking. These behaviors currently lack representation as BCI targets compared to physical activity and nutrition. However, such interventions need to overcome the several challenges involved such as identifying restriction breaches, enforcing rules in the real world, and achieving acceptance among users.

Fifth, researchers should conduct more field studies to understand mid- and long-term behavior change, especially in comparison to current face-to-face interventions. At this stage, DHR evaluation primarily relies on laboratory experiments on specific design decisions. While these studies provide important knowledge to disentangle cause-and-effect relationships under controlled conditions, we need complementary studies to evaluate DHR effectiveness in the real world. The real-world context would also allow researchers to include additional stakeholders (e.g., policymakers in the planning and evaluation stages) and, thus, potentially better address larger target populations in more realistic settings. Given the focus on changing an individual's health behavior, one would need to capture the real-world BCI's interdisciplinary context. Researchers need to effectively investigate the effect DHRs may have on behavior change compared to the current standard of care, such as face-to-face interventions. While two studies have so far analyzed digital counseling with a DHR in contrast to face-to-face interventions with human advisors (Johnston et al., 2012; King et al., 2020), future studies should especially also focus on extending the knowledge in this field to provide further insights into the social relationship that emerges with users (e.g., empathy, caring).

Sixth, behavior change is not easy. Many people struggle to change their behavior even if they cognitively understand that they can and that their current behavior harms their health. Indeed, that struggle explains why researchers examine how systems can support behavior change. However, to date, we lack knowledge on the contexts, conditions, and situations that make SNAP-related behavior change particularly challenging. Having such knowledge would allow researchers to target DHRs and their intended use patterns towards systematically reducing these challenges or respecting their influence on DHRs' design and potential effect. Thus, we suggest future research to identify such challenging contexts, conditions, and situations and their interrelation with DHRs.

Finally, our review shows that future research on DHR-facilitated health behavior change should aim for more abstract (mid-range) theories. Many studies report on specific DHR designs in particular contexts. While we need such studies for the field to mature, such an overly narrow focus leads to a somewhat disparate body of literature that does not clearly show what overarching picture one can expect with a new DHR in a new context. We believe that the field would benefit from more abstract approaches that use context, BCI, target behaviors, and the like in their theorizing. For example, one could take the existence of DHR design features and BCIs as independent variables, the extent and durability of health behavior change as the dependent variable, and the health context (smoking, nutrition, etc.) as moderating variables. With this paper, we make a step towards integrating extant knowledge regarding DHR for health behavior change. At the same time, we leave ample opportunity for primary design-oriented and empirical research to advance to more abstract theorizing.

5.4 Boundary Conditions

In our review, we examined studies that have used DHRs to deliver BCI in the SNAP domain. Hence, we explicitly excluded robots as well as avatars or agents with no human representation (e.g., virtual animals or mythical creatures). Furthermore, we focused on healthy populations to maintain comparability among the different studies without considering special needs (i.e., physical or psychological impairments related to a specific health condition). Moreover, our results pertain only to the SNAP domain and, hence, one must take care in transferring our findings to other areas. Reviewing DHRs' social design impact in other areas may also yield valuable findings for DHRs in health behavior change. We focused on covering a broad range of publications across different databases with our search string. Hence, we decided on a relatively simple search string involving various terms used across the literature. We cannot rule out that we missed a relevant publication. However, we note that we additionally engaged in snowballing, which led to five additional publications. Hence, we have confidence that our review covers many publications on the subject matter.

In particular, the COM-B model's strength lies in its broad applicability for understanding behavior change in various settings and helping one select general intervention functions (Hendriks et al., 2014; Smits et al., 2018). We built on this broad applicability to structure the different types of interventions in extant research. However, given the COM-B model's broad applicability, we note that we have not addressed all the complex relationships between capability, motivation, opportunity, and behavior. For instance, as Noorbergen et al. (2019) have indicated, an environmental restructuring intervention may not only directly affect a person's physical opportunity to engage in healthy eating habits but also indirectly affect a person's motivation. Further, the COM-B model received criticism for not including the "crucial emotional element of wanting" as a connection between intention and behavior (Marks, 2020). While one could argue that one can see "wanting" as a part of psychological skills, one should not neglect it in evaluating interventions post hoc as it helps one to understand study participants' initial situation and internalized drivers for participation. The COM-B model has also received criticism for being "too broad" to provide specific guidance for selecting intervention functions and for not indicating which policymakers one should include in developing new interventions (Hendriks et al., 2014). As a result, the COM-B model's application in practice can be time-consuming and lengthy, especially when analyzing questionnaires, and despite providing clear guidance (Ojo et al., 2019).

6 Conclusion

DHRs such as avatars and embodied agents have seen increasing use for delivering BCIs that target modifiable risk factors of a person's health behavior in the SNAP domain. Based on a structured literature review, our study summarizes the current body of knowledge on the influence that avatars' and embodied agents' social design features have on BCIs in the SNAP domain. While we found increasing evidence for DHRs' general effectiveness in facilitating health behavior change overall, further research needs to better understand how DHRs compare to alternative ways to deliver BCIs. Further, existing research on DHRs in this context primarily focuses on physical activity and nutrition while smoking and alcohol overconsumption have only received limited research attention. We hope that researchers and practitioners will find the results helpful as a frame of reference for informing DHR-based interventions' social design and evaluating their effectiveness.

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Appendix A: Overview of all Reviewed Papers

Table A1. Summary of all Reviewed Papers

Author(s) (Year)	Publication	Publishing category	DHR design (social role, physical, psychological, language)	Psychological constructs	Intervention types	Targeted behavior	Experiment information
Bickmore (2005a)	*Interacting with Computers*	J, Q3 (HCI)	EA: exercise advisor | 2D, dynamic, upper body | mimics, speech | synthetic voice	Satisfaction, repetitiveness, friendliness, trust, informativeness, liking, ease of use, relationship (empathy)	EDU, PERS, ENAB, ENVR, INC	PA (*, 2m, pedometer, intention to use)	Field (21)
Bickmore (2005b)	*Patient Education and Counseling*	J, Q1 (Medicine)	EA: exercise advisor | 2D, dynamic, face | eyebrow raises, gaze, posture shifts, nods (relational vs. non-relational) | synthetic speech	Liking, relatedness, usefulness, caring, honesty	EDU, PERS, ENAB	PA (*, 1w, pedometer, intention to use)	Field (91)
de Rosis et al. (2006)	*Journal of Biomedical Informatics*	J, Q1 (Health Informatics)	EA: dietary expert [WOz] | 3D, dynamic, head | mimics, speech | synthetic voice	Credibility, plausibility, clarity, usefulness, persuasiveness, sincerity, likeability, naturality, intelligence, competence	PERS	Nutrition	Lab (30)
van Vugt et al. (2006)	*Intelligent Virtual Agents*	C (B-rank)	EA: health advisor| 2D, static, full-body | - | text bubble	Similarity, valence, distance, aesthetics, realism, ethics (trustworthiness & credibility)	EDU	PA, Nutrition (intention to use)	Survey (278)
Bickmore et al. (2007)	*Persuasive Technology*	C (B-rank)	EA: health advisor | 2D, dynamic, face only | gaze, lips, eyebrows, nods, posture | text bubble	Politeness, annoying	EDU, PERS, ENVR	PA (*, instant rest time, intention to use)	Lab (29)
Fox et al. (2009)	*Presence: Teleoperators and Virtual Environments*	J, Q3 (HCI)	AV: virtual self | 3D, dynamic, full body | - | -	Presence	PERS, MOD	Nutrition (*, instant food choice)	Lab (69)
Fox (2009)	*Media Psychology*	J, Q1 (Applied Psychology)	AV: virtual self / other | 3D, dynamic, full-body | - | -	Resemblance	COE, INC, MOD, TRA	PA (*, 1d, self-reported activity)	Lab (63) Lab (60) Lab (75)
Jin (2009)	*CyberPsychology & Behavior*	J, Q1 (Applied Psychology)	AV: ideal/actual self | 3D, dynamic, full-body | gestures, mimics | -	Interactivity, immersion, attractiveness	PERS	Nutrition	Lab (126)
Mazzotta et al. (2009)	*Intelligent Virtual Agents*	C (B-rank)	EA: dietary expert | 3D, dynamic, head | mimics, speech | synthetic voice	Satisfaction, helpfulness, easiness, persuasiveness, reliability, validity	PERS	Nutrition	Lab (60)
Peng (2009)	*Health Communication*	J, Q1 (Health)	EA+AV: virtual self & health-conscious college students, a school dietitian, a personal trainer at the gym, and cafeteria workers | 2D, static, face only | - | text box	Enjoyment, credibility	EDU, TRA, MOD	PA, Nutrition (efficacy)	Lab (40)
Schulman & Bickmore (2009)	*Proceedings of the 4th International Conference on Persuasive Technology*	C (B-rank)	EA: health counselor | 2D, dynamic, full-body | gestures, eye movement, facial emotion | synthesized speech, text	Persuasiveness, competence, honesty, trustworthiness, boldness	EDU, PERS, ENAB	PA	Lab (47)
van Vugt et al. (2009)	*International Journal of Human Computer Studies*	J, Q1 (HCI)	EA: health advisor | 2D, static, full-body | - | text bubble	Involvement, interpersonal distance, perceived similarity, perceived ethics (trustworthiness & credibility)	EDU	PA, Nutrition (intention to use)	Survey (80) Survey (259)
Bickmore et al. (2010)	*Applied Artificial Intelligence*	J, Q3 (AI)	EA: exercise counselor | 2D, dynamic, upper body | gestures, mimics | MC answers, pedometer	Repetitiveness, enjoyment, honesty	EDU, PERS, ENAB	PA (*, 188-267d, 5-37d, pedometer, intention to use)	Field (24) Field (26)

Author(s) (Year)	Publication	Publishing category	DHR design (social role, physical, psychological, language)	Psychological constructs	Intervention types	Targeted behavior	Experiment information
Creed & Beale (2012)	*Interacting with Computers*	J, Q3 (HCI)	EA: nutrition coach | 3D, dynamic, face | mimics, speech | recorded voice	Likeability, caring, trustworthiness, perceived intelligence, positivity, supportedness	EDU, PERS, ENAB, ENVR	Nutrition	Survey (50)
Johnston et al. (2012)	*Proceedings of the Annual Hawaii International Conference on System Sciences*	C (A-rank)	EA+AV: ideal/actual self in group intervention with agents | 3D, dynamic, full-body | ? | text	-	EDU, TRA, PERS, ENAB, MOD, ENVR	PA, Nutrition (*, 12w, weight loss compared to f2f interv.)	Field (54)
Kim & Sundar (2012b)	*Computers in Human Behavior*	J, Q1 (HCI)	EA+AV: CDC agent, ideal/actual self | 3D, dynamic, full body | gestures | text field, MC answers	Attractiveness, vividness of body perception (presence), perceived risk	EDU, PERS, MOD	PA, Nutrition, smoking, alcohol (*, instant coupon choice)	Lab (69)
Watson et al. (2012)	*Journal of Medical Internet Research*	J, Q1 (Health Informatics)	EA: PA coach | 2D, dynamic, full-body | gestures, gaze | synthetic speech	Satisfaction	EDU, TRA, PERS, ENAB	PA (*, 12w, pedometer)	Field (70)
Bickmore et al. (2013a)	*Patient Education and Counseling*	J, Q1 (Medicine)	EA: health counselor | 2D, dynamic, upper body | gestures, gaze | synthetic speech	Satisfaction, ease of use	EDU, PERS, ENAB	PA, Nutrition (*, 2m, pedometer, self-report, intention to use)	Field (122)
Bickmore et al. (2013b)	*Journal of the American Geriatrics Society*	J, Q1 (Geriatrics)	EA: exercise coach | 2D, dynamic, full body | gestures, facial emotions | synthetic speech	Satisfaction, helpfulness	EDU, PERS, ENAB	PA (*, 2m, 12m, pedometer)	Field (263)
King et al. (2013)	*Journal of Health Communication*	J, Q1 (Health)	EA: virtual PA advisor | 2D, dynamic, upper body | gestures, facial emotion | synthetic speech	Caring, social distance, credibility, ease of use	EDU, PERS, ENAB	PA (*, 4m, pedometer, intention to use)	Field (40)
Klaassen et al. (2013a)	*Journal on Multimodal User Interfaces*	J, Q2 (HCI)	EA: health professional | 2D, static, upper body | gestures & body animations | synthesized voice, text	Pragmatic quality, hedonic quality, attractiveness	PERS, ENAB	PA	Field (9)
Klaassen et al. (2013b)	*ACM International Conference Proceeding Series, International Conference on Pervasive Technologies Related to Assistive Environments*	C (unranked)	EA: health professional | 2D, static, upper body | gestures & body animations | synthesized voice, text	Enjoyment, credibility, naturality, enthusiasm, glanceability	PERS, ENAB	PA	Field (14)
Lisetti et al. (2013)	*ACM Transactions on Management Information Systems*	J, Q1 (CS)	EA: alcohol counselor | 3D, dynamic, upper body | gestures, mimics (empathic vs non-empathic vs text) | synthetic voice	Empathy, anthropomorphism, animacy, likeability, intelligence, trust, social presence, usefulness, enjoyment, ease of use, sociability, anxiety, social influence, safety	EDU, PERS, ENVR, ENAB	Alcohol (intention to use)	Lab (81)
Morie et al. (2013)	*Distributed, Ambient, and Pervasive Interactions*	C (unranked)	AV: virtual self | 3D, dynamic, full-body | - | -	Similarity	MOD	PA (*, 1d, self-report)	Survey (143)
Napolitano et al. (2013)	*Journal of Diabetes Science and Technology*	J, Q1 (Bioengineering)	AV: actual self | 3D, dynamic, full-body | - | recorded voice (instructor voice)	Satisfaction	EDU, PERS, MOD	PA, Nutrition (*, 1m, confidence, self-efficacy, weight loss)	Field (8)
Song et al. (2013)	*Computers in Human Behavior*	J, Q1 (HCI)	AV: actual/future self | 2D, static, full body with photo face | - | -	Identification, perceived susceptibility	MOD, COE, PERS	Smoking (intention to quit)	Lab (62)
Ahn et al. (2014b)	*Intelligent Virtual Agents*	C (B-rank)	AV: virtual self / other | 3D, dynamic, full body | - | -	Personal relevance, self-presence	MOD, COE	Nutrition (risk perception)	Lab (47)

Author(s) (Year)	Publication	Publishing category	DHR design (social role, physical, psychological, language)	Psychological constructs	Intervention types	Targeted behavior	Experiment information
Friederichs et al. (2014)	*Journal of Medical Internet Research*	J, Q1 (Health Informatics)	EA: coach | 2D, dynamic, upper body | - | text bubble	Personal relevance, trustworthiness, appreciation	PERS, ENAB	PA (*, 1m, self-report)	Field (958)
Kim et al. (2014)	*Computers in Human Behavior*	J, Q1 (HCI)	AV: virtual self | 3D, dynamic, full body | -	Presence, enjoyment	TRA	PA (*, heart rate, intention to change)	Lab (119)
Li et al. (2014)	*Games for Health Journal*	J, Q1 (Health)	AV: virtual self | 3D, dynamic, full body | ? | -	-	TRA, PERS	PA (intention to exercise)	Lab (140)
Peña & Kim (2014)	*Computers in Human Behavior*	J, Q1 (HCI)	AV: virtual self & virtual other | 3D, dynamic, full body | - | -	-	TRA, PERS	PA (*, activity sensors)	Lab (94)
Schmeil & Suggs (2014)	*Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*	J, Q2 (Computer Science)	AV: actual/future self | 3D, dynamic, full body | - | -	Perc. healthiness	PERS, MOD	PA, Nutrition (motivation, intention to change)	Survey (512)
Vainio et al. (2014)	*Proceedings of the 8th International Conference on Pervasive Computing Technologies for Healthcare*	C (unranked)	EA: supporter | 2D, static, face only | mimics | speech bubble	-	TRA, PERS, ENAB	PA, Nutrition (*, 1m, self-report)	Field (66)
Yasavur et al. (2014)	*Journal on Multimodal User Interfaces*	J, Q2 (HCI)	EA: alcohol counselor | 3D, dynamic, upper body | mimics | synthetic voice	Likeability, annoyance, habitability, accuracy, ease of use	EDU. PERS, ENAB	Alcohol (intention to use)	Lab (89)
Ahn (2015)	*Health Communication*	J, Q1 (Health)	AV: virtual self / other | 3D, dynamic, full body | - | -	Social distance, temporal distance, involvement	MOD, COE	Nutrition (*, 1w, self-report)	Lab (73)
Friederichs et al. (2015)	*International Journal of Behavioral Nutrition and Physical Activity*	J, Q1 (Medicine)	EA: coach | 2D, dynamic, upper body | eye/head movements, gestures | text bubble	-	PERS, ENAB	PA (*, 12m, self-report)	Field (4302)
Thomas et al. (2015)	*Journal of Diabetes Science and Technology*	J, Q1 (Bio-engineering)	EA+AV: Self-avatar, other agents and coach | 3D, dynamic, full body | gestures |speech	Credibility, usefulness, ease of use	EDU, TRA, PERS, ENAB	PA, Nutrition (confidence, commitment to change)	Lab (37)
Waddell et al. (2015)	*Cyberpsychology Behavior and Social Networking*	J, Q1 (Applied Psychology)	AV: virtual self | 3D, dynamic, full-body | - | -	Similarity	MOD, PERS	PA (*, instant coupon choice, exercise intentions)	Lab (132)
Andrade et al. (2016)	*Studies in Health Technology and Informatics*	J, Q3 (Health Informatics)	AV: fixed male | 3D, dynamic, upper body | - | -	Immersion, satisfaction	PERS	Smoking (intention/motivation to quit)	Lab (60)
Behm-Morawitz et al. (2016)	*Cyberpsychology, Behavior and Social Networking*	J, Q1 (Applied Psychology)	AV: virtual self (others in intervention) | 3D, dynamic, full-body | - | text	Self-presence, inspiration	MOD, ENAB	PA, Nutrition (*, 4w, efficacy, self-report)	Field (90)
Li & Lwin (2016)	*Computers in Human Behavior*	J, Q1 (HCI)	AV: virtual self | 2D & 3D, dynamic, full body | gestures, facial expression | -	Self-presence, identification, enjoyment	TRA, PERS	PA (intention to exercise, intention to use)	Lab (322)
Peña et al. (2016)	*Journal of Computer-Mediated Communication*	J, Q1 (CS Applications)	AV: virtual self & virtual other| 3D, dynamic, full body | - | -	Similarity	PERS, ENAB, MOD	PA (*, activity during game)	Lab (96)
Thompson et al. (2016)	*Games for Health Journal*	J, Q1 (Health)	AV: actual self | 3D photo, dynamic, full-body | - | -	Similarity, game appeal	PERS, ENAB	PA	Lab (47)

Author(s) (Year)	Publication	Publishing category	DHR design (social role, physical, psychological, language)	Psychological constructs	Intervention types	Targeted behavior	Experiment information
Gardiner et al. (2017)	*Patient Education and Counseling*	J, Q1 (Medicine)	EA: nutrition & PA coach | 2D, dynamic, upper body | - | synthetic voice	Satisfaction	EDU, TRA, ENAB	Smoking, Nutrition, Alcohol, PA (*, 1m, self-efficacy, confidence, self-report, intention to use)	Field (61)
Joo & Kim (2017)	*Interacting with Computers*	J, Q3 (HCI)	AV: fixed female |3D, dynamic, full-body | smile | -	Healthiness	MOD	PA, Nutrition (*, instant cookie consumption, step count)	Lab (124)
Lyles et al. (2017)	*JMIR Serious Games*	J (unranked)	AV: ideal/actual self | 3D, dynamic, full-body | - | -	Representativeness	MOD	PA, Nutrition (intention to use)	Lab (42)
Sah et al. (2017)	*Media Psychology*	J, Q1 (Applied Psychology)	AV: ideal/ought/actual self | 3D, dynamic, full-body | - | -	Health consciousness	MOD, PERS	Nutrition (*, instant food choice)	Lab (133)
Zhou et al. (2017)	Proceedings of the International Conference on Culture and Computing, Culture and Computing	C (unranked)	EA: PA coach | 3D, dynamic, upper body | mimics, gestures | synthetic voice	Liking, trust, satisfaction, easiness, social distance, caring	EDU, PERS, ENAB	PA (intention to use)	Lab (49)
Abdullah et al. (2018)	*Journal of Epidemiology and Global Health*	J, Q3 (Epi-demiology)	EA: virtual coach | 2D, dynamic, upper body | mimics, speech | synthetic voice	Helpfulness, easiness, lifelikeness, friendliness, caring, knowledgeability, satisfaction, usefulness	EDU, INC, PERS, ENVR, ENAB	Smoking (*, 2w, intention to quit)	Field (6)
Oyibo et al. (2018)	Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization	C (B-rank)	EA: virtual coach | 2D, dynamic, full-body | - | text box	Persuasiveness	TRA, MOD, ENAB	PA (self-efficacy, self-regulation, outcome expectations)	Survey (673)
Fuchs et al. (2019)	Proceedings of the 13th Biannual Conference of the Italian SIGCHI Chapter: Designing the next Interaction	C (unranked)	AV: future self | 2D, static, full-body | smile, gaze, blink | text boxes	-	EDU, COE, MOD, PERS, ENAB	Nutrition, Alcohol (*, 8d, self-report)	Field (67)
Olafsson et al. (2019)	ACM International Conference Proceeding Series, International Conference on Pervasive Computing Technologies for Healthcare	C (unranked)	EA: nutrition/PA counselor | 3D, dynamic, upper body | facial cues, gestures, gaze | synthetic voice	Trust, likeability, knowledgeability, naturality, similarity, satisfaction	EDU, PERS, ENAB	PA, Nutrition (self-efficacy, intention to use)	Lab (39)
King et al. (2020)	*JAMA Internal Medicine*	J, Q1 (Internal Medicine)	EA: virtual advisor | 3D, dynamic upper body | facial cues, gestures, gaze | synthetic voice	Satisfaction, helpfulness	EDU, TRA, PERS, ENAB	PA (*, 12m, pedometer steps, self-report (activity, sedentary time), vital parameters)	Field (245)
Koulouris et al. (2020)	*CHI Conference on Human Factors and Computing Systems*	C (A*)	AV: actual / ideal / future self | 3D, dynamic, full body | - | -	Identification, enjoyment	TRA, MOD, INC	PA (*, cycling power)	Lab (15) Lab (16) Lab (17)
Maher et al. (2020)	*JMIR MHealth and UHealth*	J, Q2 (Health Informatics)	EA: virtual coach | 2D static, face | - | text field	-	EDU, TRA, PERS, ENAB	PA, Nutrition (*, 12w, PA survey, self-reported food intake)	Field (31)

Author(s) (Year)	Publication	Publishing category	DHR design (social role, physical, psychological, language)	Psychological constructs	Intervention types	Targeted behavior	Experiment information
Mohan et al. (2020)	*ACM Transaction on Interactive Intelligent Systems*	J, Q2 (HCI)	EA: virtual coach | 2D, static, upper body | - | text	-	TRA, ENAB	PA (*, 6w, self-report)	Field (21)
Murali et al. (2020)	*International Conference on Autonomous Agents and Multiagent Systems*	C (A*-rank)	EA: exercise promotion agent | 3D, dynamic, upper body | facial cues, gestures, gaze | synthetic voice	Satisfaction, social distance	EDU, PERS, ENAB	PA (self-efficacy)	Lab (40)
Navarro et al. (2020a)	*International Journal of Environmental Research and Public Health*	J, Q2 (Public Health)	AV: ideal/actual self | 3D, dynamic, full body | - | -	Enjoyment, anxiety, presence, similarity, identification	MOD, ENAB	PA (*, 1w, self-report)	Field (42)
Navarro et al. (2020b)	*Health Communication*	J, Q1 (Health)	AV: virtual self / other | 3D, dynamic, full body | - | -	Similarity	MOD	PA (*, cardiac frequency, step count)	Lab (305)
Olafsson et al. (2020)	*International Conference on Intelligent Virtual Agents*	C (B-rank)	EA: nutrition/PA counselor | 3D, dynamic, upper body | facial cues, gestures, gaze | synthetic voice	Satisfaction, trust, likeability, knowledgeability, naturality, similarity, humor	EDU, PERS, ENAB	PA, Nutrition (Motivation, continuation of agent use)	Lab (15)

Notes: journal ranks based on the Scimago Journal and Country Rank (https://www.scimagojr.com/); conference rankings based on the Computing Research and Education (CORE) ranking (http://portal.core.edu.au/conf-ranks/). A star (*) in the "targeted behavior" column indicates that the study investigated actual behavior change (either self-reported or measured with sensors) followed by the period of time (d = days, w = weeks, m = months). EDU = education, TRA = training, COE = coercion, INC = incentivization, MOD = modelling, PERS = persuasion, ENVR = environmental restructuring, ENAB = enablement.

Appendix B: Summary of Risk of Bias Analysis

To deliver further critical insight into the reported experiments, we conducted a risk of bias analysis using the risk of bias 2 tool (RoB 2 tool; Sterne et al., 2019). The RoB 2 tool allows one to assess the risk of bias in randomized controlled trials that compare interventions' effects (Sterne et al., 2019). Hence, we could consider only the 43 papers that conducted randomized controlled trials in the assessment. The 17 papers excluded from the RoB assessment mainly appeared in computing (11 papers) and health outlets (6 papers). They represent feasibility studies or single group user tests that investigated perceptions and behavior change pre- and post-intervention. Even though we could not analyze these papers with the RoB 2 tool, we consider the findings in these studies as relevant as they present important user feedback for implementing DHRs in SNAP behavior change.

In the analysis, we paid particular attention to assessing the risk of bias across the five main RoB 2 tool categories overall. Such an assessment can indicate findings' overall reliability (we show individual results of the RoB 2 tool assessment of the 43 papers (from 47 different randomized controlled trial studies) in Appendix C). Given the interdisciplinary nature of the studies in our sample, we considered each study's broader discipline based on its outlet (i.e., computing, health, or psychology). As Sterne et al. (2019) have proposed, the risk of bias assessment in the single categories can guide what limitations exist in randomized controlled trials to support efforts to design and implement future studies. Based on our analysis, we observed that, for all five risk of bias areas (e.g., randomization process), the majority of studies exhibited "low risk". We found that 14 studies reached an overall low risk of bias since they received a "low risk" rating in all five risk areas (Bickmore et al., 2013a, 2013b; Creed & Beale, 2012; Fox et al., 2009; Friederichs et al., 2015; Gardiner et al., 2017; Joo & Kim, 2017; Kim et al., 2014; King et al., 2020, 2013;Li et al., 2014; Navarro et al., 2020b; Peña et al., 2016; Watson et al., 2012). However, we also observed "some concerns" for 16 studies in their randomization and 13 studies in terms of the selection of results. Interestingly, the differentiation along the disciplines shows that these concerns appeared more severe for computing and psychology publications than for health. Half of the computing (13 out of 26) and 57 percent of the psychology (4 out of 7) studies exhibited "high risk" in how they measured the outcome, while all of the health studies (14 out of 14) exhibited "low risk". Similarly, the studies with "some concerns" or even "high risk" in their randomization and the selection of the reported results predominantly came from the computing or psychology disciplines. Taken together and in line with Sterne et al. (2019), this analysis can guide researchers in limiting the risk of bias in future studies (e.g., by considering the research design of the studies that yielded low risk of bias).

Table B1. Summary of Risk of Bias Analysis Across the Five Different RoB2 Areas

Bias risk	Discipline	Randomization process	Deviations from intended interventions	Missing outcome data	Measurement of the outcome	Selection of the reported result
Low risk	Computing	10	22	21	10	16
	Health	12	13	10	14	13
	Psychology	5	3	6	3	1
Some concerns	Computing	12	4	4	3	7
	Health	2	1	4	-	1
	Psychology	2	3	1	-	5
High risk	Computing	4	-	1	13	3
	Health	-	-	-	-	-
	Psychology	-	1	-	4	1

We found a higher bias risk in computing and psychology studies compared to studies published in health outlets. Among other aspects, this risk related to missing information on the randomization process. Researchers inherently rely on objective, quantified measurements for outcomes. To achieve that, they should use validated survey scales when measuring psychological constructs. However, we sometimes found that, in computing and psychology outlets in particular, this was not always the case. Nonetheless, those publications that yielded a higher risk of bias in one or more categories or that we could not evaluate with the RoB 2 tool provided important insight into using DHRs for BCI delivery in SNAP. Hence, researchers should not discard the insights that these studies provide. Based on these insights, future DHR studies need to consider how they disclose information on the randomization process and the selection and reporting of outcomes. Regarding the risk of bias due to missing outcome data, we can report that most studies, especially lab studies, had many available outcomes reported for randomized study participants. For longer field studies, we identified attrition as a more prominent topic, which leads to higher requirements for analyzing dropouts.

Overall, researchers need to consider the health domain-specific requirements for randomized controlled trials and other study types that they need to plan into the study protocol from the beginning. Our RoB 2 tool analysis showed that computing and psychology studies exhibited a higher risk of bias in their randomization, outcome measurement, and selection of reported results compared to studies published in health outlets. Given the inherent focus of these studies on health behavior change, the multidisciplinary audience requires detailed information about how the study design addresses the five different risk of bias areas. The study design needs to meet the health-specific evaluation requirements of the presented DHRs. Notably, a total of 14 studies exhibited a low risk level across all RoB 2 categories and may, hence, serve as a guide for designing randomized controlled trial evaluation studies.

Appendix C: Detailed Results of Risk of Bias Analysis

Table C1. Detailed Results of Risk of Bias Analysis with Risk of Bias 2 Tool

Study	Publishing category	Randomization process	Deviations from intended interventions	Missing outcome data	Measurement of the outcome	Selection of the reported result
Bickmore et al. (2005a)	Computing	Some concerns	Some concerns	Some concerns	Low	Some concerns
Bickmore et al. (2005b)	Health	Low	Low	Some concerns	Low	Low
de Rosis et al. (2006)	Computing	Could not assess				
van Vugt et al. (2006)	Computing	High	Low	Low	High	High
Bickmore et al. (2007)	Computing	Could not assess				
Fox et al. (2009)	Computing	Low	Low	Low	Low	Low
Fox & Bailenson (2009): lab study 1	Psychology	Low	Some concerns	Low	Low	Some concerns
Fox & Bailenson (2009): lab study 2	Psychology	Low	Low	Low	High	High
Fox & Bailenson (2009): lab study 3	Psychology	Low	Low	Low	High	Some concerns
Jin (2009)	Psychology	Low	Some concerns	Low	High	Some concerns
Mazzotta et al. (2009)	Computing	Some concerns	Some concerns	Low	High	Low
Peng (2009)	Health	Low	Low	Some concerns	Low	Some concerns
Schulman & Bickmore (2009)	Computing	Low	Low	Low	High	Low
van Vugt et al. (2009): survey 1	Computing	Low	Low	Some concerns	High	Some concerns
van Vugt et al. (2009): survey 2	Computing	Low	Low	Low	Some concerns	Low
Bickmore et al. (2010): field report 1	Computing	Some concerns	Low	High	Some concerns	High
Bickmore et al. (2010): field report 2	Computing	Some concerns	Low	Low	Low	Some concerns
Creed & Beale (2012)	Computing	Low	Low	Low	Low	Low
Johnston et al. (2012)	Computing	High	Low	Some concerns	Low	Low
Kim & Sundar (2012)	Computing	Some concerns	Low	Low	High	Low
Watson et al. (2012)	Health	Low	Low	Low	Low	Low
Bickmore et al. (2013a)	Health	Low	Low	Low	Low	Low
Bickmore et al. (2013b)	Health	Low	Low	Low	Low	Low
King et al. (2013)	Health	Low	Low	Low	Low	Low
Klaassen et al. (2013a)	Computing	Could not assess				
Klaassen et al. (2013b)	Computing	Could not assess				
Lisetti et al. (2013)	Computing	Some concerns	Low	Low	Low	Low
Morie et al. (2013)	Computing	High	Low	Low	High	Low

Study	Publishing category	Randomization process	Deviations from intended interventions	Missing outcome data	Measurement of the outcome	Selection of the reported result
Napolitano et al. (2013)	Health	Could not assess				
Song et al. (2013)	Computing	Some concerns	Low	Low	High	Some concerns
Ahn et al. (2014b)	Computing	Low	Some concerns	Low	High	High
Friederichs et al. (2014)	Health	Some concerns	Low	Some concerns	Low	Low
Kim et al. (2014)	Computing	Low	Low	Low	Low	Low
Li et al. (2014)	Health	Low	Low	Low	Low	Low
Peña & Kim (2014)	Computing	Some concerns	Low	Low	Low	Low
Schmeil & Suggs (2014)	Computing	Some concerns	Some concerns	Low	High	Some concerns
Vainio et al. (2014)	Computing	High	Low	Some concerns	High	Some concerns
Yasavur et al. (2014)	Computing	Could not assess				
Ahn (2015)	Health	Some concerns	Low	Some concerns	Low	Low
Friederichs et al. (2015)	Health	Low	Low	Low	Low	Low
Thomas et al. (2015)	Health	Could not assess				
Waddell et al. (2015)	Psychology	Some concerns	Some concerns	Low	Low	Some concerns
Andrade et al. (2016)	Computing	Some concerns	Low	Low	High	Some concerns
Behm-Morawitz et al. (2016)	Psychology	Low	High	High	Low	Some concerns
Li & Lwin (2016)	Computing	Could not assess				
Peña et al. (2016)	Computing	Low	Low	Low	Low	Low
Thompson et al. (2016)	Health	Could not assess				
Gardiner et al. (2017)	Health	Low	Low	Low	Low	Low
Joo & Kim (2017)	Computing	Low	Low	Low	Low	Low
Lyles et al. (2017)	Health	Could not assess				
Sah et al. (2017)	Psychology	Some concerns	Low	Low	High	Low
Zhou et al. (2017)	Computing	Some concerns	Low	Low	High	Low
Abdullah et al. (2018)	Health	Cannot be assessed				
Oyibo et al. (2018)	Computing	Could not assess				
Fuchs et al. (2019)	Computing	Could not assess				
Olafsson et al. (2019)	Computing	Some concerns	Low	Low	Some concerns	Low
King et al. (2020)	Health	Low	Low	Low	Low	Low
Koulouris et al. (2020)	Computing	Could not assess				

Study	Publishing category	Randomization process	Deviations from intended interventions	Missing outcome data	Measurement of the outcome	Selection of the reported result
Maher et al. (2020)	Health	Could not assess				
Mohan & Venkatakrishnan (2020)	Computing	Could not assess				
Murali et al. (2020)	Computing	Low	Low	Low	High	Low
Navarro et al. (2020a)	Health	Low	Some concerns	Low	Low	Low
Navarro et al. (2020b)	Health	Low	Low	Low	Low	Low
Olafsson et al. (2020)	Computing	Could not assess				

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