Understanding Personalization for Health Behavior Change Applications: A Review and Future Directions

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Abstract:

Health behavior change (HBC) applications hold much promise for promoting healthy lifestyles, such as enhancing physical activity (PA), diet, and sleep. Incorporating personalization strategies is seen as key to designing effective HBC applications. However, researchers and application designers lack knowledge about the different kinds of personalization strategies, how to implement them, and what strategies work. Thus, we reviewed prior empirical studies on personalization for HBC applications and developed a framework to synthesize the prior studies we identified and to provide an integrative view of the personalization strategies, their inputs, and outcomes. Our findings suggest that researchers have much potential to conduct design research that employs demographic and contextual characteristics for personalization and that examines personalization strategies that target HBC applications' interface and channels. In terms of implementation and adoption, we call for researchers to examine unaddressed issues such as low adherence and contextual barriers for these applications. We also suggest that researchers need to systematically examine the effects of specific personalization strategies on their efficacy. Other than providing an integrative view of extant studies, our study contributes by outlining key directions for future research in this area.

Keywords: Personalization, Health Behavior Change Applications, Literature Review, User and Contextual Characteristics, Research Framework, Future Research Agenda.

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1 Introduction

There has been increasing interest in developing *health behavior change (HBC)* applications, which refer to sociotechnical information systems (IS) that focus on forming or changing attitudes and behaviors related to a healthy lifestyle voluntarily (Lehto & Oinas-Kukkonen, 2015). Unhealthy behaviors, such as physical inactivity, calorie-rich diets, and insufficient sleep, continue to rise and constitute key risk factors associated with chronic diseases (Bauer, Briss, Goodman, & Bowman, 2014), which account for more than 70 percent of global deaths (GBD 2017 DALYs and HALE Collaborators, 2017). HBC applications, as a form of e-health IS, hold much promise for promoting healthy behaviors (Wilson & Strong, 2014) with commercial investment in e-health increasing 14-fold from 2010 to US$14.6B in 2018 (StartUp Health Insights, 2018). HBC application designers acknowledge that individuals have unique characteristics that will likely influence their responses to HBC interventions (i.e., the actions or elements through which the applications aim to improve health behaviors) (Kreuter, Farrell, Olevitch, & Brennan, 2000). Thus, researchers have advocated for a personalized approach whereby one individualizes HBC interventions for recipients (Lehto & Oinas-Kukkonen, 2015).

Personalization, which researchers often use synonymously with the term tailoring (as in this paper)[1], refers to any strategy and information that one intends to reach a specific person based on characteristics that uniquely pertain to that person, that relate to the outcome of interest, and that one derives from an individual assessment (Kreuter et al., 2000). In the human-computer interaction (HCI) and IS fields, researchers have mostly investigated personalization in the e-commerce (e.g., to provide personalized product/service recommendations, comparisons, or interactions) (e.g., Tam & Ho, 2005) and e-education contexts (e.g., to provide tailored learning approaches) (e.g., Peña-Ayala, Sossa, & Méndez, 2014). However, personalization for HBC applications differs from these other contexts in several ways. First, HBC applications typically track user behaviors for personalization (e.g., past behaviors) continuously 24 hours a day, seven days a week (Chen, Zhu, Chen, & Li, 2018) as opposed to the episodic tracking (during search/purchase, or learning activities) in the other contexts (Adomavicius & Tuzhilin, 2005; Essalmi, Ayed, Jemni, & Graf, 2010). Second, personalization strategies for HBC often involve setting and reviewing goals and giving evaluative feedback (op den Akker, Jones, & Hermens, 2014), which could have relevance for the e-education context (Ashman et al., 2014) but not for e-commerce personalization. Last, most importantly, HBC is a long-term (potentially life-long) process that requires continuous self-regulatory efforts (Morrison, 2015) unlike the target behaviors in the other two contexts. Thus, extant research in e-commerce and e-education may not directly pertain to personalization for HBC applications, which serves as one motivation for our study.

Personalized HBC applications have employed various technologies, such as browser (e.g., websites) and messaging (e.g., short-message service (SMS)) technologies (Lustria, Cortese, Noar, & Glueckauf, 2009). For example, browser-based applications provide websites where users can input and track their diet over time, while a messaging application can remind users via text about how much exercise they need to do to achieve their daily goals. More recently, with the rise in ubiquitous technologies (e.g., smartphones and wearables), mobile applications for HBC have gained ground (Chen et al., 2018). These applications typically use sensors to record users' health behaviors continuously (e.g., daily steps) for personalization.

While a personalized approach can outperform a "one-size-fits-all" approach in promoting health behaviors (Krebs, Prochaska, & Rossi, 2010; Lustria et al., 2013), inadequate personalization represents a key concern for individuals who use mobile health (m-health) applications, and researchers have cited it as a reason for non-adherence (Vo, Auroy, & Sarradon-Eck, 2019). Furthermore, e-health (including m-health) application designers lack knowledge about different kinds of personalization strategies, how to implement them, and what strategies work (Deloitte, 2017). Researchers have also suggested that we need to improve on and further examine personalized HBC applications needs improvement (e.g., Lehto & Oinas-Kukkonen, 2015). More broadly, researchers have highlighted IS personalization as an important theme for future research under the IS design science and HCI paradigms (Reinecke & Bernstein, 2013; Arazy, Nov, & Kumar, 2015).

Prior studies have examined the effectiveness of particular personalized HBC applications, such as one for increasing physical activity (PA) (e.g., Friederichs, Bolman, Oenema, Verboon, & Lechner, 2016) and

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[1] Some researchers (e.g., Lehto & Oinas-Kukkonen, 2015) have distinguished personalization from tailoring. While Lehto and Oinas-Kukkonen (2015) defined personalization as adapting to a "user" and tailoring as adapting to a "user group", they noted that the two terms closely relate to each other and that researchers often use the two terms interchangeably.

another for following a healthy diet (e.g., Orji, Vassileva, & Mandryk, 2014). However, we do not comprehensively understand different kinds of user characteristics, personalization strategies for HBC applications, their theoretical foundations, and how they may work. Such knowledge would prove valuable for both researchers and practitioners in this area. In this regard, some studies have reviewed the literature on personalized HBC applications but have focused on 1) evaluating the effectiveness of such applications in aggregate through meta-analyses (Krebs et al., 2010; Lustria et al., 2013) and 2) reviewing studies restricted to specific conditions, such as weight loss (Ryan, Dockray, Linehan, 2019) and diabetes self-management (Sahin, Courtney, Naylor, & Rhodes, 2019). Further, such studies (Krebs et al., 2010; Lustria et al., 2009; Lustria et al., 2013; Ryan et al., 2019; Sahin et al., 2019) reviewed research that used browser-based and/or messaging technologies for delivering personalized HBC interventions without covering mobile apps, which have become the dominant technology for such personalization (Blandford, 2019). Further, authors conducted these prior reviews in the medical and health informatics fields, which (understandably so) do not focus on these applications' design. Thus, there is a lack of research that has reviewed prior studies on personalization of HBC applications (including mobile technologies) while synthesizing the knowledge to better understand this topic and outline directions for future research.

Motivated thus, the objective of this study is to provide an integrative review of research on personalization in HBC applications in order to identify the various personalization strategies that such applications have employed, the user characteristics and theories used to design these strategies, and the outcomes and effects of personalization. We also focus on uncovering promising directions for future research on designing and implementing these applications and on their adoption and impact. Specifically, we review empirical research published from January, 2014, to December, 2018 on implementing personalization in HBC applications for three major health behaviors: PA, diet, and sleep (Wagner & Brath, 2012; Kankanhalli, Saxena, & Wadhwa, 2019).

The paper proceeds as follows: in Section 2, we propose and describe a research framework for synthesizing research on personalization in HBC applications. In Section 3, we discuss the research method we followed to conduct our literature review. In Section 4, we present the findings from our review. In Section 5, we outline an agenda for future research in this area. In Section 6, we discuss the study's limitations and conclude the paper.

2   Research Framework

HBC applications have the potential to provide personalized health interventions to a large number of users (Blandford, 2019). Researchers sometimes view personalization as a feature of an HBC application (Lehto & Oinas-Kukkonen, 2015). However, as an HBC application usually has multiple features, and some features can either work the same for all users (i.e., generic features) or adapt to each user (i.e., personalized features) (Kaptein, Markopoulos, de Ruyter, & Aarts, 2015), we view personalization as an approach to implement a feature. For example, one can implement a fitness HBC application's feedback feature in a generic way (e.g., the application sends the message "More than 80% of users have completed their exercise goals today" to all users) or a personalized way (e.g., it sends the message "You have achieved 80% of your exercise goal" to the specific users who satisfied the condition). Accordingly, we refer to the personalization approaches that one employs for implementing various features as personalization strategies.

To develop our research framework, we built on a common way to view e-commerce personalization (Adomavicius & Tuzhilin, 2005). We adapted this view due to the lack of personalization frameworks for HBC applications given that extant perspectives predominantly focus on HBC systems in general (e.g., Kelders, Oinas-Kukkonen, Oörni, & van Gemert-Pijnen, 2016). Adomavicius and Tuzhilin (2005) suggest that carrying out personalization comprises three stages: 1) understanding the consumer (or user), 2) delivering personalized offerings, and 3) measuring the personalization's effect. As per this perspective, we identified three key elements for personalizing HBC applications: 1) user characteristics employed for personalization, 2) personalization strategies for providing interventions to users, and 3) personalization outcomes. User characteristics for personalization help one understand users. Personalization strategies constitute ways to offer interventions through designing features based on users' characteristics. Outcomes constitute the consequences that one evaluates to assess personalization's effects. By elaborating on these three elements using relevant HBC personalization concepts, we propose a holistic research framework to synthesize knowledge from our reviewed studies.

2.1 Framework Elements

2.1.1 User/Contextual Characteristics

We identified four types of user characteristics employed for such personalization. We drew three types from Armanasco, Miller, Fjeldsoe, and Marshall (2017): demographic, behavioral, and psychological characteristics. To those three, we added the contextual characteristics category from the m-health personalization literature (e.g., Klein, Manzoor, Middelweerd, Mollee, & te Velde, 2015). We checked that our typology covered all the user characteristics that the studies we reviewed used for personalization. First, demographic characteristics, such as age, gender, and race, have been employed to personalize HBC interventions. Second, researchers have also employed behavioral characteristics, such as past health behaviors (e.g., past PA history), task performance, and goal achievement, to make HBC interventions personally relevant (Short, Rebar, Plotnikoff, & Vandelanotte, 2015). Third, psychological variables (e.g., cognitive perceptions, attitudes, intention, and self-efficacy) derived from psychological theories have been used to identify target individuals who will be more receptive to certain HBC interventions (Klein et al., 2015; Nikoloudakis et al., 2018). Other examples of psychological characteristics include individual preferences and motivations. Last, contextual characteristics capture users' environmental information that pertains to, but lies outside, users, such as physical and social environmental characteristics. These characteristics (e.g., location, weather, nearby exercise facilities) have also been employed to design personalized HBC interventions (Klein et al., 2015). Researchers have used all these characteristic types to implement personalization strategies because they can influence individuals' psycho-social beliefs, such as their preferences and needs with respect to HBC (Brug, Oenema, & Campbell, 2003).

2.1.2 Personalization Strategies

To identify the types of personalization approaches for our framework, we first examined prior studies that have classified HBC personalization strategies. As an early effort, Hawkins, Kreuter, Resnicow, Fishbein, and Dijkstra (2008) proposed three strategy types for tailoring health communication: personalization[2], feedback, and content matching. Subsequently, Dijkstra (2016) extended Hawkins et al.'s (2008) classification by adding two more types: source matching and exposure matching. While these authors intended these classifications for health behaviors in general, op den Akker et al. (2014) drew from the literature on tailored PA coaching systems to propose a typology of personalization strategies for PA. Though their typology overlaps significantly with Dijkstra's (2016) categorization, op den Akker et al. (2014) added the category goal setting. Researchers have recognized goal setting to play an important role in translating health intentions to actions (Ziegelmann, Lippke, & Schwarzer, 2006) and reported that it does so more effectively when one tailors it to individuals (Baretta et al., 2019). Furthermore, prior research has highlighted the potential for gamification (i.e., using game elements in non-game contexts) to motivate HBC (Ryan, Rigby, & Przybylski, 2006). While earlier game designs for HBC adopted a "one-size-fits-all" approach (e.g., Orji, Mandryk, Vassileva, & Gerling, 2013), researchers have increasingly personalized gamification for HBC (e.g., Orji, Mandryk, & Vassileva, 2017). Thus, we added goal-setting and gamification strategies to Dijkstra's (2016) classification.

Subsequently, we synthesized the strategies that commonly appeared (though they may have had different labels) across these previous classifications to derive our categorization and coding scheme for personalization strategies. First, Orji et al. (2014) identified 10 personalization strategies that can be used for gamification designs (though some did not pertain specifically to games). For example, Orji et al.'s (2014) "suggestion" strategy, which provides personalized suggestions to recipients, resembles Dijkstra's (2016) "recommendation matching" strategy. Orji et al.'s (2014) "customization" strategy, which provides personalized functionality to recipients, resembles Dijkstra's (2016) "matching engagement" strategy. Thus, we removed suggestion and customization and instead used Dijkstra's (2016) corresponding strategies. Second, we included personalization strategies that researchers have not classified before but have appeared in previous studies. For example, we added feedforward, a strategy that provides information about users' future conditions based on their input characteristics (Dhaliwal & Benbasat, 1996). We define and show the sources for the resulting 18 personalization strategies (after synthesizing them) in Table 1.

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[2] Hawkins et al. (2008) used the term "tailoring" to refer to various forms of individualization, which other studies considered "personalization" (e.g., Adomavicius & Tuzhilin, 2005), including in our study.

Table 1. Personalization Strategies and Their Classification

Personalization strategy	Definition	Source	Personalization object
Identification	Mention the users' identity information (e.g., include their name in the message)	Dijkstra (2016), Hawkins et al. (2008), op den Akker et al. (2014)	Content
Contextualization	Personalize the message to the context that is meaningful to the user (e.g., weather)	Dijkstra (2016), Hawkins et al. (2008), op den Akker et al. (2014)	Content
Raising expectation	Raise users' expectation that the content is especially meant for them (e.g., answer their question on the website)	Dijkstra (2016), Hawkins et al. (2008), Op den Akker et al. (2014)	Content
Recommendation matching	Provide recommendation or advice matched to the user's preferences (e.g., way of thinking(	Dijkstra (2016)	Content
Value matching	Personalize the messages to things that users value or that motivate them (e.g., a social cause)	Dijkstra (2016)	Content
Descriptive feedback	Provide users with their own data descriptions without any evaluation or interpretation (e.g., how much distance covered in exercise)	Hawkins et al. (2008), op den Akker et al. (2014)	Content
Evaluative feedback	Provide information about evaluation or interpretation on users' data (e.g., how much exercise they did compared to a daily guideline)	Hawkins et al. (2008), op den Akker et al. (2014)	Content
Feedforward	Predict and provide information about users' future state before they decide on a behavior (e.g., calories burnt if they ran 5 kilometers)	Dhaliwal & Benbasat (1996)	Content
Matching engagement	Present users with matched system features in order to stimulate their engagement (e.g., which features a particular user finds most useful)	Dijkstra (2016)	Interface
Matched timing	Contact users at appropriate time points	Dijkstra (2016)	Channel
Matched intensity	Contact users with a preference-matched frequency, length, and intensity	Dijkstra (2016)	Channel
Messenger matching	Send messages to users using a matched source (e.g., friend or family)	Dijkstra (2016)	Channel
Testimonial matching	Find a matched witness/expert who gives a testimonial on a topic to users	Dijkstra (2016)	Channel
Goal initializing	Allow users to set personalized short-term or long-term health behavior goals	op den Akker et al. (2014)	Functionality
Goal reviewing	Allow users to modify adaptively personalized goals or plans during the intervention over time	op den Akker et al. (2014)	Functionality
Competition	Allow users to compete (e.g., take part in a contest) with preferred users to perform the desired behavior	Orji et al. (2014)	Functionality
Reward	Offer personalized virtual (e.g., praise) or material (e.g., financial) rewards to users for performing the target behavior	Orji et al. (2014)	Functionality
Comparison	Allow users to view and compare their performance with preferred others' performance	Orji et al. (2014)	Functionality

Finally, we organized the 18 personalization strategies into higher-level categories for better understanding. To do so, we employed a common IS personalization view (Fan & Poole, 2006) that previous IS studies have used (e.g., Wu, Im, Tremaine, Instone, & Turoff, 2003) including in the healthcare context (e.g., Kocaballi et al., 2019). As per their view (Fan & Poole, 2006), one can classify personalization strategies according to personalization object (what is personalized), subject (who does the personalization), and target (to whom to personalize). We adopted the personalization object as our categorization criterion for two reasons. First, this criterion provides useful information for IS design, which fits one of our research purposes of shedding light on the design of personalization for HBC applications. Second, it makes sense to organize our strategies by this criterion because these strategies have only one personalization "target" (i.e., the application user) and involve one "subject" (i.e., the HBC intervention). Fan and Poole (2006) identified four personalization objects in IS: the information content (content), the way information is presented (interface), the information delivery (channel), and the module that a user can manipulate (functionality). Drawing on their work, we classified our 18 personalization strategies into these four categories (see the last column in Table 1).

2.1.3 Personalization Outcomes

The outcomes that one expects from implementing personalization in HBC applications constitute the third element in our framework. Drawing from prior HBC review studies, we identified four outcome categories; 1) health status outcomes, 2) adherence outcomes (Lentferink et al., 2017), 3) psychosocial outcomes, and 4) health behavior change outcomes (Lau, Lau, Wong, & Ransdell, 2011). As before, we validated the typology against the outcomes that the studies we reviewed assessed. First, application designers often initially focus on adherence, which refers to the extent to which users engage with a HBC application (Kelders, Kok, Ossebaard, & Gemert-Pijnen, 2012) (e.g., how frequently they use it and for how long) because only when the application engages users and they adhere to it (keep using it) would it have a chance to influence their behaviors (Lentferink et al., 2017). Second, given that psychosocial outcomes constitute factors that significantly determine health behavior (e.g., self-efficacy, attention), HBC applications have also been designed to stimulate a change in such variables (op den Akker et al., 2014). Thus, the extent to which HBC applications change users' psychosocial variables constitutes another type of outcome to evaluate personalization effects. Interestingly, researchers have used some of these variables (e.g., self-efficacy) to personalize HBC applications. Third, HBC constitutes the major outcome of interest in most such applications since they ultimately focus on achieving it. Health behavior change (e.g., an increase in PA, improved diet, better sleep quality) intuitively indicates desirable outcomes. Last, researchers have often measured the health status after such interventions as an outcome (e.g., weight, BMI, mental health).

We integrated the three elements that we describe above and their subcategories to derive our research framework for synthesizing studies on personalization for HBC applications (see Figure 1). The user and contextual characteristics are used for implementing the personalization strategies, which influence the outcomes. We derived the moderating relationships in the figure and psychosocial states' mediating effects from our review. We discuss them in more detail in Section 4.
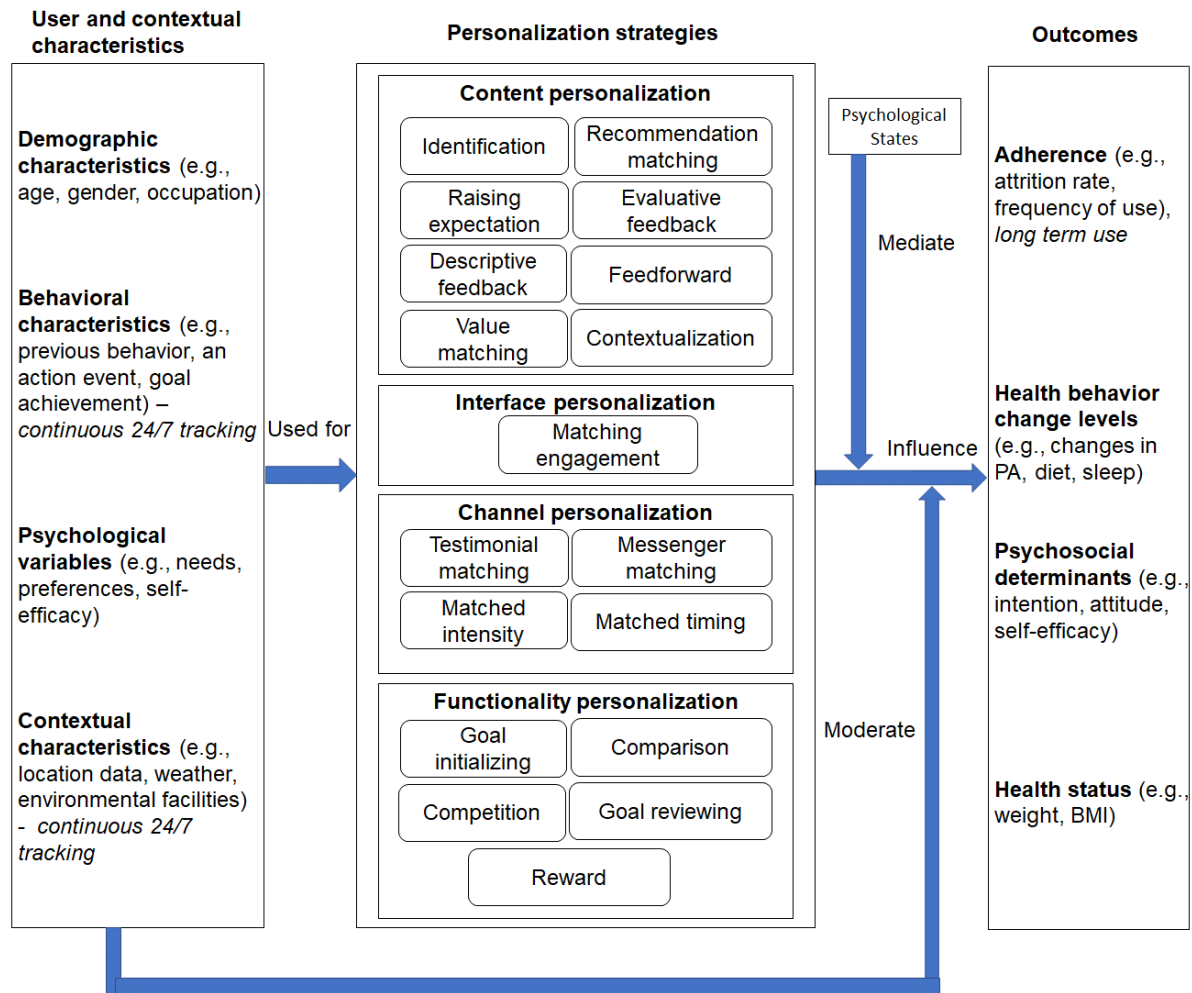
Figure 1. Proposed Research Framework

3   Literature Selection Method

We developed selection criteria to thoroughly search for papers relevant to our topic. First, we excluded studies that recruited diseased participants since we did not focus on disease management and clinic care studies in this study. Second, studies needed to aim to change/improve the key health behaviors (i.e., PA, diet, and sleep). We chose these three behaviors as they represent the main lifestyle dimensions that affect the general population's health (Wagner & Brath, 2012; Kankanhalli et al., 2019). Third, we searched for studies with a publish date from January, 2014, to December, 2018. We considered papers from this period for two reasons: 1) prior research has already identified personalization strategies before 2014 (op den Akker et al., 2014; Dijkstra, 2016) and 2) key technologies for HBC applications, such as wearable devices and mobile apps, emerged around 2014 (Patel, Asch, & Volpp, 2015), which provides a significant opportunity for designing new personalization strategies that we do not understand well. Fourth, studies needed to report results for at least one of the four types of outcomes in our proposed framework so that we could assess personalization outcomes. Finally, we included only peer-reviewed papers (excluding reviews) in English. We considered only peer-reviewed journals papers as a quality check (relative to conference papers). Note that, in our review, we focused on literature in both the medical/health informatics and IS/HCI fields because research on HBC applications crosses domains and needs interdisciplinary knowledge and collaboration (Kennedy et al., 2012).

According to the above selection criteria, we formulated the search query as: *"(personaliz* OR personalis* OR tailor* OR customis* OR customiz*) AND ("physical activity" OR "physical activities" OR exercis* OR fitness OR diet OR eating OR sleep*) AND (mobile OR virtual OR web OR Internet OR smartphone)" AND (intervention).* We used this query to search eight databases with publications that cover this area: ACM

Digital Library, AISeL, EBSCOhost, IEEExplore, PsycINFO, PubMed, Scopus, and Web of Science. We set the date range to 1 January, 2014, to 31 December, 2018. When a database's search engine permitted it, we limited the search results to peer-reviewed journal papers with full text available in English. Finally, we included relevant studies that the searched papers cited to form our initial search results set (i.e., we additional papers from the initial ones we identified).

We show the process that we followed to select and screen papers with the PRISMA flow chart (Moher, Liberati, Tetzlaff, Altman, & Prisma Group, 2009) in Figure 2. In the screening stage, we excluded 1) duplicate papers, 2) non-journal papers, 3) papers in a language other than English, 4) review papers, 5) qualitative studies, and 6) papers that did not pertain to the HBC topic. In the eligibility stage, we excluded studies that: 1) did not report relevant outcomes, 2) did not conduct health interventions, 3) did not implement personalization strategies, and 4) that authors conducted via human-human interaction rather than technology-human interaction (not m-health/e-health studies). The first and second authors performed the whole process. These two authors randomly checked 10 percent of the papers together first to ensure that they agreed on the exclusion criteria. All authors discussed and resolved any disagreements.
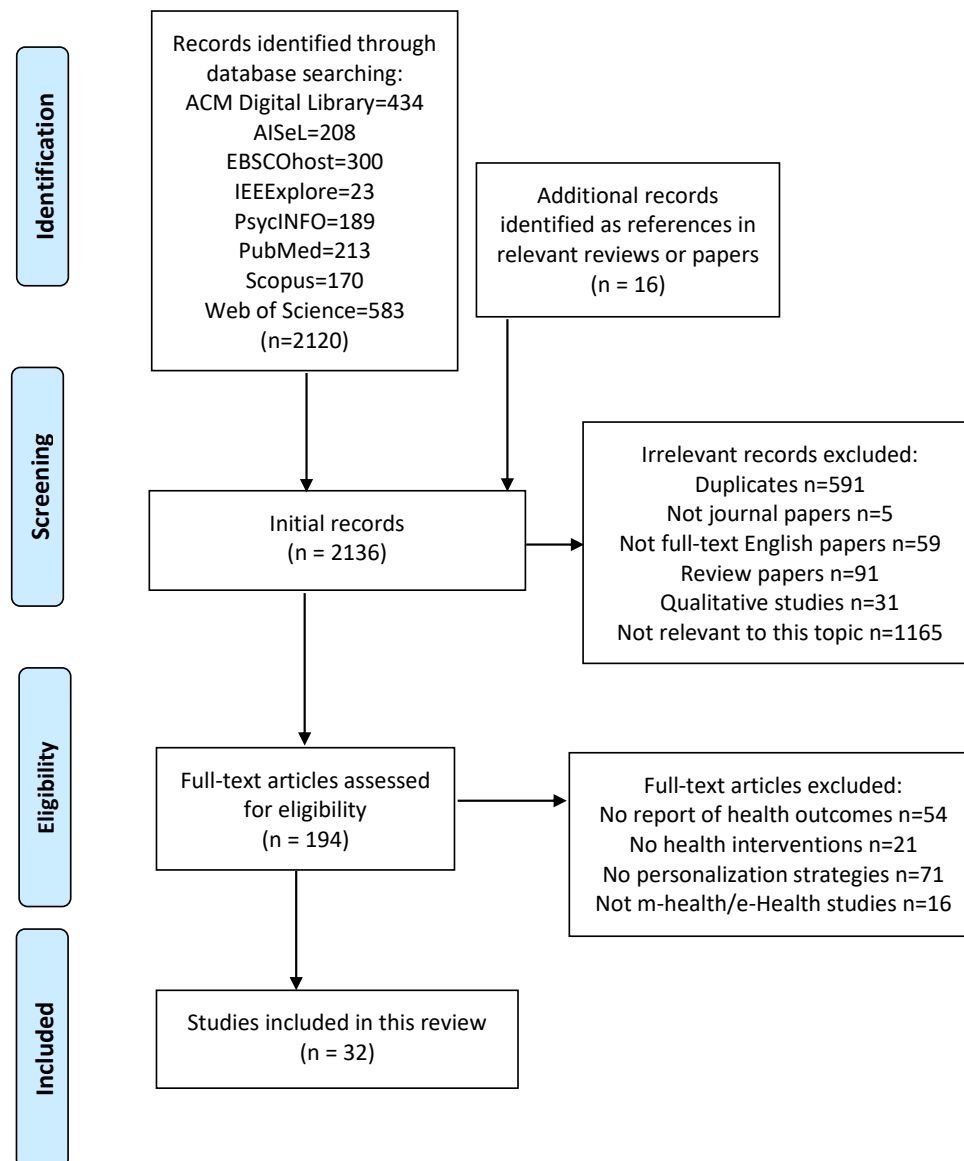

Figure 2. PRISMA Flow Chart for the Paper-selection Process

4   Review Findings

We identified 32 eligible papers the end of the selection process (we present each paper and their details in the Appendix). First, we present general observations for the papers according to their publication outlet, research methods, and delivery technologies. Subsequently, we discuss our findings regarding personalization strategies and their inputs, theoretical bases for designing the personalization strategies, and personalization's outcomes/effectiveness (for aggregate and individual strategies).

4.1   General Observations

Thirteen journals from the medical and health informatics fields published 21 papers in our sample, while seven journals from the IS and HCI fields published the remaining 11 (we mark these latter papers with an asterisk). The *Journal of Medical Internet Research* published the most papers (9) followed by *Computers in Human Behavior* (4) and *User Modeling and User-Adapted Interaction* (2). The remaining 17 journals published one paper each.

As for the research method that the studies adopted, we found that 23 studies (72%) used randomized controlled trials (RCTs). Two studies (6%) used a pre-post design with no control group, two used online experiments, and two used laboratory experiments. One study used a randomized pilot trial, one used mixed methods (survey and interview), and one used an online survey.

As for the delivery technologies that the studies used for their personalized interventions (based on our classification in Section 1), 12 studies (38%) used a website (either research-specific or commercial), six studies (19%) used messaging technologies (SMS, email, wearable device display, and voice messages), while another six used mobile apps (either research-specific or commercial). The other eight studies (25%) used multiple technologies by combining websites with messaging technologies or mobile apps.

4.2   Personalization Strategies and Their Inputs

We present the personalization strategies and their corresponding user/contextual characteristics employed that the studies we reviewed employed in Table 2. We define and classify these strategies in Table 1. Most studies (29 / 91%) implemented content personalization strategies, while half employed functionality personalization strategies (16 studies / 50%). Less than half implemented channel personalization strategies (10 studies / 31%), and only seven (22%) implemented interface personalization strategies.

As Table 2 shows, most studies employed users' behavioral characteristics (25 studies, 78%). A significant number employed (19 / 59%) employed psychological characteristics, while less than half (14 / 44%) employed demographic characteristics. Only five studies (16%) employed contextual characteristics. Thus, we found that researchers have used all four characteristic types to personalize HBC applications' content and channel. However, we found that they have not used demographic and psychological characteristics for interface personalization or demographic characteristics for functionality personalization. We next discuss each personalization strategy category in detail.

Table 1. Personalization Strategies and Characteristics Employed

Personalization strategy type	Demographic characteristics (14)	Behavioral characteristics (25)	Psychological characteristics (19)	Contextual characteristics (5)
Content (29)	**Identification**: name (Alley, Jennings, Plotnikoff, & Vandelanotte, 2016; Compernolle, Vandelanotte, Cardon, de Bourdeaudhuij, & de Cocker, 2015; Kaptein et al., 2015; Kattelmann et al., 2014; Soetens, Vandelanotte, de Vries, & Mummery, 2014; Wang et al., 2015) **Recommendation matching**: gender, age, BMI (Alamri et al., 2014), race (Joseph, Keller, Adams, & Ainsworth, 2015), job title, chronotype (Van Drongelen et al., 2014), not known (Alley et al., 2016; Friederichs et al., 2016; Soetens et al., 2014) **Evaluative feedback**: age, BMI (Soetens et al., 2014)	**Contextualization**: goal achievement (Solenhill et al., 2016), engagement behavior (Kim, Lee, & Han, 2018) **Recommendation matching**: past health behaviors (Alamri et al., 2014; Alley et al., 2016; Friederichs et al., 2016; Soetens et al., 2014; van der Mispel, Poppe, Crombez, Verloigne, & de Bourdeaudhuij, 2017; Walthouwer, Oenema, Lechner, & de Vries, 2015) **Descriptive feedback**: past health behaviors (Alamri et al., 2014; Alley et al., 2016; Compernolle et al., 2015; Elbert et al., 2016; Friederichs et al., 2016; Hoye, Boen, & Lefevre, 2015; McCreless, Goul, Louis, & Warner, 2017; Pyky et al., 2017; Samendinger, Pfeiffer, & Feltz, 2018; van der Mispel et al., 2017; Walthouwer et al., 2015; Wang et al., 2015), goal achievement (Morrison et al., 2014; Poirier et al., 2016; Soetens et al., 2014; Springvloet, Lechner, de Vries, Candel, & Oenema, 2015; Zhou et al., 2018) **Evaluative feedback**: past health behaviors (Alley et al., 2016; van Genugten, van Empelen, & Oenema, 2014), goal achievement (Adams et al., 2017; Compernolle et al., 2015; Friederichs et al., 2016; Joseph et al., 2015; McCreless et al., 2017; Morrison et al., 2014; Solenhill et al., 2016; Zhou et al., 2018), task performance (Achterkamp, Hermens, & Vollenbroek-Hutten, 2015; Kim et al., 2018) **Feedforward**: past health behaviors (Alamri et al., 2014; McCreless et al., 2017;	**Contextualization**: personal preferences (Elbert et al., 2017; Li & Mao, 2015) **Recommendation matching**: psychosocial determinants (Alley et al., 2016; Compernolle et al., 2015; Elebrt et al., 2016; Friederichs et al., 2016; Soetens et al., 2014), stage of change (Compernolle et al., 2015; Hebden, Cook, van der Ploeg, King, & Allman-Farinelli, 2014; Kattelmann et al., 2014; Soetens et al., 2014) **Value matching**: motivations (Smith, Morgan, Plotnikoff, & Dally, 2014) **Descriptive feedback**: psychosocial determinants (Elbert et al., 2016; Friederichs et al., 2016; Springvloet et al., 2015; Walthouwer et al., 2015)	**Recommendation matching**: location and surrounding environment (Friederichs et al., 2016; Soetens et al., 2014) **Descriptive feedback**: location and surrounding environment (Springvloet et al., 2015)
Interface (7)	**Matching engagement**: gender (Hebden et al., 2014), gamer type (Orji et al., 2017, 2014)		**Matching engagement**: personality (Lepri, Staiano, Shmueli, Pianesi, & Pentland, 2016; McCreless et al., 2017), personal preferences (Hebden et al., 2014; Morrison et al., 2014), stage of change (Pyky et al., 2017)	
Channel (10)	**Testimonial matching**: gender (Elbert et al., 2016) **Matched intensity**: race (Joseph et al., 2015)	**Matched timing**: engagement behavior (Adams et al., 2017; Alley et al., 2016; Kattelmann et al., 2014; van Drongelen et al., 2014)	**Messenger matching**: Personal preferences (Poirier et al., 2016; Walthouwer et al., 2015) **Matched timing**: personal preferences (Morrison et al., 2014; Wang et al., 2015)	**Matched timing**: location and surrounding environment (van Drongelen et al., 2014)

Table 1. Personalization Strategies and Characteristics Employed

Functionality (16)		**Goal initializing**: past health behaviors (Alley et al., 2016; Pyky et al., 2017) **Goal reviewing**: past health behaviors (Adams et al., 2017; Joseph et al., 2015; Poirier et al., 2016; van Genugten et al., 2014; Zhou et al., 2018) **Comparison**: past health behaviors (Pyky et al., 2017; Samendinger et al., 2018) **Reward**: past health behaviors (Pyky et al., 2017), goal achievement (Kim et al., 2018; Morrison et al., 2014; Pyky et al., 2017), engagement behavior (Poirier et al., 2016; Pyky et al., 2017), task performance (Kim et al., 2018)	**Goal initializing**: psychosocial determinants (Friederichs et al. 2016; Morrison et al., 2014; Smith et al., 2014; van Genugten et al., 2014; Walthouwer et al., 2015), personal preferences (Kattelmann et al., 2014; Springvloet et al., 2015; van der Mispel et al., 2017) **Goal reviewing**: personal preferences (Alley et al., 2016; Springvloet et al., 2015; van der Mispel et al., 2017; Walthouwer et al., 2015)	**Goal initializing**: location and surrounding environment (Alley et al., 2016)

Note: numbers in the brackets next to headings indicate the number of studies in each column/row. We do not present strategies for which researchers did not specify the characteristics they used to implement them (i.e., raising expectations (Compernolle et al., 2015) and recommendation matching (Kaptein et al., 2015; Solenhill et al., 2016)) in this table.

4.2.1   Content Personalization

Content personalization, which involves tailoring HBC message content that an application sends to recipients, attracted the most interest in the studies we reviewed (29 out of 32). These strategies include simply mentioning the recipient's name (i.e., identification), telling the recipient that the message is personalized (i.e., raising expectation), making the messages more personally relevant based on recipient's context or values (i.e., contextualization and value matching), and providing tailored health recommendations and feedback (i.e., recommendation matching, descriptive feedback, evaluative feedback, and feedforward).

The user and contextual characteristics employed varied across the content personalization strategies (see Table 2). Studies implemented the identification strategy based only on recipients' names (Alley et al., 2016; Compernolle et al., 2015; Kaptein et al., 2015; Kattelmann et al., 2014; Soetens et al., 2014; Wang et al., 2015). They implemented contextualization by adapting the conversation form or communication style to recipients' self-reported preferences (Elbert et al., 2016; Li & Mao, 2015) and by presenting recipients with different icons (e.g., a smiley face) according to their self-evaluated goal achievement (Solenhill et al., 2016) and engagement (Kim et al., 2018) levels. One study (Smith et al., 2014) leveraged *value matching* by sending motivational messages about physical activity's benefits in accord with recipients' self-reported motivations. Studies leveraged recommendation matching to tailor recommendations (e.g., how to be more active) to various user and contextual characteristics, such as demographics (e.g., gender, age, BMI, job title, chronotype) (Alamri et al., 2014; Alley et al., 2016; Friederichs et al., 2016; Joseph et al., 2015; Soetens et al., 2014; van Drongelen et al., 2014), behavioral (mainly past health behaviors) (Alamri et al., 2014; Alley et al., 2016; Friederichs et al., 2016; Soetens et al., 2014; van der Mispel et al., 2017; Walthouwer et al., 2015), psychological (e.g., stage of change, perceived cons and pros, self-efficacy) (Compernolle et al., 2015; Elbert et al., 2016; Friederichs et al., 2016; Hebden et al., 2014; Kattelmann et al., 2014; Soetens et al., 2014), and contextual (e.g., location, environment) (Friederichs et al., 2016; Soetens et al., 2014) characteristics. Descriptive and evaluative feedback strategies provided recipients with their information without and with evaluations, respectively. The information in descriptive feedback included recipients' past health behaviors (Alamri et al., 2014; Alley et al., 2016; Compernolle et al., 2015; Elbert et al., 2016; Friederichs et al., 2016; Hoye et al., 2015; McCreless et al., 2017; Pyky et al., 2017; Samendinger et al., 2018; van der Mispel et al., 2017; Walthouwer et al., 2015; Wang et al., 2015), goal-achievement levels (Morrison et al., 2014; Poirier et al., 2016; Soetens et al., 2014; Springvloet et al., 2015; Zhou et al., 2018), psychological factors (e.g., motivations for losing weight) (Elbert et al., 2016; Friederichs et al., 2016; Springvloet et al., 2015; Walthouwer et al., 2015), and environmental conditions (e.g., the availability and prices of healthy food products nearby) (Springvloet et al., 2015). The information in evaluative feedback included motivational feedback about health risks related to users' age and BMI (Soetens et al., 2014) and evaluations about their behavioral performance (Achterkamp et al., 2015; Adams et al., 2017; Alley et al., 2016; Compernolle et al., 2015; Friederichs et al., 2016; Joseph et al., 2015; Kim et al., 2018; McCreless et al., 2017; Morrison et al., 2014; Solenhill et al., 2016; van Genugten et al., 2014; Zhou et al., 2018). In

contrast to feedback that provides past information, the feedforward strategy offered information about expected future situations, such as a predicted gain/loss for individual recipients if they continued their current behavior (Alamri et al., 2014; McCreless et al., 2017).

4.2.2   Interface Personalization

Interface personalization focuses on tailoring the way in which an application presents HBC-related information to recipients. Among the studies we reviewed (see Table 2), some—particularly IS/HCI studies (Lepri et al., 2016; McCreless et al., 2017; Orji et al., 2017, 2014; Pyky et al., 2017)—used one such strategy (i.e., matching engagement) to design HBC application interfaces and present suitable system features to recipients. Most designed interventions for recipients of different personalities (Lepri et al., 2016; McCreless et al., 2017) and gamer types (Orji et al., 2017, 2014) and analyzed which system features persuaded specific recipient types more. Two medical informatics studies implemented matching engagement by allowing recipients to configure system features according to gender and/or personal preferences (Hebden et al., 2014; Morrison et al., 2014).

4.2.3   Channel Personalization

Channel personalization involves tailoring the media through which HBC applications communicate with recipients. These strategies target communication's source (i.e., messenger matching and testimonial matching), timing (i.e., matched timing), and contact frequency (i.e., matched intensity). In the studies we reviewed (see Table 2), messenger matching involved sending messages to recipients via their preferred delivery technology and mode (email/website, or video/text) (Poirier et al., 2016; Walthouwer et al., 2015). Elbert et al. (2016) implemented testimonial matching by constructing stories that recounted individuals' successful personal experiences with HBC and sharing them with recipients based on their gender. For matched timing, several studies sent reminders to follow an intervention to recipients when they did not engage with the system for a period (Adams et al., 2017; Alley et al., 2016; Kattelmann et al., 2014; van Drongelen et al., 2014), when they preferred to receive them (Morrison et al., 2014; Wang et al., 2015), or based on their location and surroundings (van Drongelen et al., 2014). To implement matched intensity, Joseph et al. (2015) set the contact frequency to three messages per week based on a prior test from which they found this frequency to best suit African American women (i.e., tailoring this strategy to recipients' race).

4.2.4   Functionality Personalization

Functionality personalization tailors what users can do with an HBC application. The studies we reviewed employed four strategies (see Table 2): goal initializing, goal reviewing, comparison, and reward. Goal initializing and goal reviewing strategies relate to goal setting. Goal initializing allows individuals to tailor their own behavioral goals, while goal reviewing provides the recipients with adaptive goals over time with respect to their current context. Among our included studies, some systems implemented goal initializing by automating suggestions about short- or long-term HBC goals or action plans based on users' past health behaviors (Alley et al., 2016; Pyky et al., 2017) and physical environments (Alley et al., 2016). However, more studies implemented this strategy by asking recipients to set their own initial goals (Friederichs et al., 2016; Kattelmann et al., 2014; Morrison et al., 2014; Smith et al., 2014; Springvloet et al., 2015; van der Mispel et al., 2017; van Genugten et al., 2014; Walthouwer et al., 2015). Some goal reviewing studies set behavior change goals adaptively based on users' past behaviors (Adams et al., 2017; Joseph et al., 2015; Poirier et al., 2016; van Genugten et al., 2014; Zhou et al., 2018), while others allowed them to modify their goals during the intervention if they wanted to (Alley et al., 2016; Springvloet et al., 2015; van der Mispel et al., 2017; Walthouwer et al., 2015). Studies implemented comparison by showing users their own progress vis-à-vis their peers' progress (Pyky et al., 2017; Samendinger et al., 2018). Studies used the reward strategy more often by giving users virtual or material incentives based on their past health behaviors (Pyky et al., 2017), whether they had achieved behavioral goals (Kim et al., 2018; Morrison et al., 2014; Pyky et al., 2017), their engagement level with the intervention (Poirier et al., 2016; Pyky et al., 2017), and their task performance (Kim et al., 2018).

4.3   Theoretical Bases for Designing Personalized Interventions

As Table 3 shows, half of the studies we reviewed (16 / 50%) employed theories to design personalized HBC interventions. Among these studies, six (19%) (Alley et al., 2016; Compernolle et al., 2015; Smith et al., 2014; Soetens et al., 2014; Springvloet et al., 2015; Walthouwer et al., 2015) used more than one theory in their design. We adopted a common HBC theory classification (Morrison, 2015) to categorize the theories that these studies used into four groups: 1) persuasion, 2) motivation, 3) volition and self-regulation, and 4) intention. This classification was suitable because it identifies different psychological elements that are crucial to HBC. To this classification, we added a fifth group that differed from the other groups: stage-based theories (Burton-Jones, McLean, & Monod, 2015).

Table 2. Theories Employed and Their Categories

Group (count)	Theory	Frequency	Studies
Persuasion theories (2)	Elaboration likelihood model	1	Alley et al. (2016)
	Similarity-attraction theory	1	Li et al. (2015)
Motivation theories (3)	Self-determination theory	3	Friederichs et al. (2016), Hoye et al. (2015), Smith et al. (2014)
Volition and self-regulation theories (6)	Social cognitive theory	2	Joseph et al. (2015), Smith et al. (2014)
	Self-regulation theory	4	Springvloet et al. (2015), van der Mispel et al. (2017), van Drongelen et al. (2014), Walthouwer et al. (2015)
Intention theories (4)	Theory of planned behavior	4	Alley et al. (2016), Compernolle et al. (2015), Soetens et al. (2014), Springvloet et al. (2015)
Stage-based theories (8)	Transtheoretical model	5	Compernolle et al. (2015), Hebden et al. (2014), Kattelmann et al. (2014), Pyky et al. (2017), Soetens et al. (2014)
	I-change model	1	Walthouer et al. (2015)
	Precaution adoption process model	1	Springvloet et al. (2015)
	Health action process approach	1	Morrison et al. (2014)

The first group focuses on persuasion, which includes the elaboration likelihood model (ELM) and similarity-attraction theory (SAT). Both these theories highlight the importance of tailored persuasion strategies in changing human behaviors. According to the ELM (Petty & Cacioppo, 1986), tailored interventions are more likely to result in durable attitude change and consequent behavior change compared to non-tailored interventions because they increase the perceived personal relevance of the intervention content, thus increasing motivation to thoughtfully (centrally) process the presented arguments. In our review, Alley et al. (2016) stated that they constructed tailored advice based on the ELM, but they did not mention how they did so. SAT (Ruijten, 2020) posits that individuals have a higher likelihood to engage with interventions that share something similar to themselves. In our review, Li and Mao (2015) designed their virtual health advisor's communication style based on SAT.

The second group focuses on users' motivations and, thus, includes the self-determination theory (SDT). SDT argues that autonomously motivated behavior is easier to realize and maintain than externally determined behaviors (Deci & Ryan, 1985). The theory proposes that autonomous motivation increases when people satisfy their emotional needs for autonomy, competence, and relatedness. Three studies (Friederichs et al., 2016; Hoye et al., 2015; Smith et al., 2014) used SDT as a guide to design HBC interventions to support participants' basic psychological needs (e.g., through providing tailored motivational messages (Smith et al., 2014) or personalized feedback (Hoye et al., 2015)).

The third group focuses on volition and self-regulation (e.g., social cognitive theory (SCT) and self-regulation theory (SRT)). SCT emphasizes the importance of self-efficacy in facilitating behavior change (i.e., people are more likely to achieve a behavior change goal when they believe it beneficial and they have the ability to achieve it) (Bandura, 1986). Joseph et al. (2015) and Smith et al. (2014) designed intervention materials

to improve SCT constructs, such as self-efficacy. SRT describes behavior change as a way in which people select a goal and provide themselves with rewards or punishments according to their goal performance (Maes & Karoly, 2005). Four studies (Springvloet et al., 2015; van der Mispel et al., 2017; van Drongelen et al., 2014; Walthouwer et al., 2015) included self-regulation techniques (e.g., personalized feedback) in their interventions.

The fourth group focuses on users' intention and, thus, includes the theory of planned behavior (TPB). The TPB proposes three elements that influence users' health behavior intention (i.e., their attitude toward behaviors, subjective norms, and perceived behavioral control) (Ajzen, 1991). Compernolle et al. (2015) and Soetens et al. (2014) provided participants with personalized feedback targeting TPB elements. Alley et al. (2016) and Springvloet et al. (2015) also designed interventions based on TPB.

While the theories in the above groups constitute variance theories (Burton-Jones et al., 2015), the last group comprised stage or phase-based theories, such as the transtheoretical model (TTM), the I-change model (ICM), the precaution adoption process model (PAPM), and the health action process approach (HAPA). The TTM (Prochaska & Velicer, 1997) posits that one can divide HBC into stages and that intervention strategies should suit users' specific needs and motivations at different stages. The studies we reviewed often used the TTM in designing advice, feedback, or health material (Compernolle et al., 2015; Hebden et al., 2014; Kattelmann et al., 2014; Pyky et al., 2017; Soetens et al., 2014). The ICM posits that behavior change results from a person's going through three phases: awareness, motivation, and action (de Vries, Mesters, Van de Steeg, & Honing, 2005). Walthouwer et al. (2015) reported using the ICM as the theoretical basis for their intervention, though they did not mention details. The PAPM explains how individuals develop their intention and decide to perform behavior change after a six-stage deliberation process (Weinstein, Sandman, & Blalock, 2008). Springvloet et al. (2015) designed a multi-module HBC intervention based on the PAPM. The HAPA describes a two-stage process that includes a pre-intentional motivation process during which people form their behavior intention and a post-intentional volition process during which they implement and maintain the intended behavior (Schwarzer, 2008). Morrison et al. (2014) used the HAPA to conceptualize and measure the effect of a goal-engagement intervention.

As the primary goal of personalization in HBC applications is to improve health behaviors, it is not surprising that most of the theories used (e.g., TTM, TPB, SRT, SCT, SDT, HAPA, HBM, PAPM, and ICM relate to the psychosocial determinants of health behavior (i.e., motivation, self-regulation, and behavior planning/intention). Only two studies (Alley et al., 2016; Li & Mao, 2015) employed theories that explain how a health communication intervention can be persuasive (e.g., ELM and SAT). Note that, except for one study (Li & Mao, 2015), we did not find studies that hypothesized, tested, and/or generated theoretical models to explain personalized HBC applications' design, implementation, adoption, and impact. In other words, authors mostly used the theories "loosely" to justify their decision to employ certain personalization strategies (e.g., descriptive feedback based on SDT (Hoye et al., 2015)) or to measure certain variables (e.g., self-efficacy based on SCT (Joseph et al., 2015)).

4.4 Outcomes and Effects of Personalization Strategies

In this section, we provide descriptive findings about outcomes the studies in our sample examined before summarizing personalization's effectiveness for aggregate and individual strategies. In total, 25 studies carried out aggregate interventions (combining multiple personalization strategies), while seven implemented a single personalization strategy.

In terms of the target health behaviors, four studies focused only on diet (13%) (Elbert et al., 2016; Orji et al., 2017, 2014, Springvloet et al., 2015), and none targeted sleep alone. Seven studies focused on changing both PA and diet (22%) (Hebden et al., 2014; McCreless et al., 2017; Morrison et al., 2014; Smith et al., 2014; van der Mispel et al., 2017; van Genugten et al., 2014; Walthouwer et al., 2015), while four studies targeted all three health behaviors (13%) (Kattelmann et al., 2014; Li & Mao, 2015; Solenhill et al., 2016; van Drongelen et al., 2014). The remaining studies focused on increasing PA alone (17 studies / 53%). No study that targeted multiple health behaviors examined the relationships among the behaviors. As one might expect, most studies (25 studies / 78%) reported outcomes regarding health behavior change levels (i.e., all studies except Alamri et al., 2014; Kaptein et al., 2015; Li & Mao, 2015; Orji et al., 2017, 2014; van der Mispel et al., 2017; van Genugten et al., 2014). Nearly half of the studies (15 studies / 47%) examined adherence outcomes (Alley et al., 2016; Compernolle et al., 2015; Elbert et al., 2016; Hebden et al., 2014; Kaptein et al., 2015; Morrison et al., 2014; Poirier et al., 2016; Smith et al., 2014; Soetens et al., 2014; Solenhill et al., 2016; van der Mispel et al., 2017; van Drongelen et al., 2014; van Genugten et al., 2014; Walthouwer et al., 2015; Wang et al., 2015; Zhou et al., 2018), while 10 studies (31%) reported

psychosocial determinants (Achterkamp et al., 2015; Alamri et al., 2014; Alley et al., 2016; Joseph et al., 2015; Li & Mao, 2015; Morrison et al., 2014; Orji et al., 2017, 2014; Pyky et al., 2017; Solenhill et al., 2016), and seven studies (22%) assessed intervention effects on health status outcomes (Alley et al., 2016; Hebden et al., 2014; Kattelmann et al., 2014; Pyky et al., 2017; Smith et al., 2014; van Drongelen et al., 2014; Walthouwer et al., 2015). Studies mostly used objective measures for adherence outcomes (the most common being retention/attrition rate and engagement/frequency of use). Authors largely calculated objective measures for adherence from archival/log data; only one study (Wang et al., 2015) used self-reported data. Regarding health behavior change outcomes, studies often used objective measures for PA but self-reported measures for diet and sleep, which indicates that researchers found these two behaviors difficult to measure objectively with erstwhile technologies. Studies used objective measures for health status more often than subjective measures (e.g., weight and waist size). Studies measured psychosocial determinants only through self-reported measures as these determinants constitute latent constructs.

4.4.1   Aggregate Effects of Personalization Strategies

Most studies we reviewed (25 / 78%) reported the effect that their respective HBC intervention had. In this section, we analyze these interventions' effectiveness as per the different personalization strategy combinations they adopted.

Four studies (Alamri et al., 2014; Compernolle et al., 2015; Soetens et al., 2014; Solenhill et al., 2016) leveraged a combination of content personalization strategies with mixed results. They all used a combination of descriptive and/or evaluative feedback and recommendation matching. In addition, Alamri et al. (2014) employed feedforward, Solenhill et al. (2016) used contextualization, and Compernolle et al. (2015) and Soetens et al. (2014) used identification. The studies assessed somewhat different outcomes: Alamri et al. (2014) looked at self-awareness and motivation to lose weight, while Solenhill et al. (2016) evaluated motivation to improve dietary and PA habits. Compernolle et al. (2015) and Soetens et al. (2014) assessed objective and self-reported PA outcomes, while Soetens et al. (2014) also measured adherence. Alamri et al. (2014) reported positive effects, while Compernolle et al. (2015) saw positive impacts in the short term but not in the long term. The remaining studies reported mixed results for different outcome variables (i.e., Soetens et al. (2014) saw positive effects for adherence but not PA, while Solenhill et al. (2016) reported positive impact on motivation for improving health habits but not on the habits themselves).

Other studies combined personalization strategies across categories in their interventions, and we discuss the results by these combinations. Specifically, two studies (Hebden et al., 2014; McCreless et al., 2017) combined content and interface personalization. Both used matching engagement combined with recommendation matching for Hebden et al. (2014) and descriptive/evaluative feedback and feedforward for McCreless et al. (2017). Hebden et al. (2014) reported non-significant effects on PA, food intake, weight, and BMI. McCreless et al. (2017) found that receiving feedback or feedforward did not influence individuals to reduce their calorie intake more than if they received either one individually.

Three studies (Elbert et al., 2016; van Drongelen et al., 2014; Wang et al., 2015) combined content and channel personalization strategies. van Drongelen et al. (2014) and Wang et al. (2015) used matched timing, Elbert et al. (2016) and Wang et al. (2015) used descriptive feedback, and Elbert et al. (2016) and van Drongelen et al. (2014) used recommendation matching. Additionally, Elbert et al. (2016) employed contextualization and testimonial matching, while Wang et al. (2015) used identification. Elbert et al. (2016) reported insignificant intervention effects on fruit and vegetable intake but found interaction effects with health status, health literacy, and intake in a pretest. van Drongelen et al. (2014) observed significant improvement in sleep quality, strenuous PA, and snacking behavior but no effect on moderate PA and health perceptions. Last, Wang et al. (2015) found that their intervention promoted PA for only one week and reduced engagement. We noted that different studies assessed different outcomes for PA, diet, or sleep. We also saw that they mostly reported interventions as effective in the short run.

One fourth of the studies (Friederichs et al., 2016; Kim et al., 2018; Samendinger et al., 2018; Smith et al., 2014; Springvloet et al., 2015; van der Mispel et al., 2017; van Genugten et al., 2014; Zhou et al., 2018) combined content and functionality personalization in their interventions. These studies commonly used descriptive feedback (Elbert et al., 2016; Samendinger et al., 2018; Springvloet et al., 2015; van der Mispel et al., 2017; Zhou et al., 2018), evaluative feedback (Elbert et al., 2016; Kim et al., 2018; van Genugten et al., 2014; Zhou et al., 2018), goal initializing (Elbert et al., 2016; Smith et al., 2014; Springvloet et al., 2015; van der Mispel et al., 2017; van Genugten et al., 2014), and goal review (Springvloet et al., 2015; van der Mispel et al., 2017; van Genugten et al., 2014; Zhou et al., 2018). Additionally, studies employed contextualization (Kim et al., 2018), recommendation matching (Elbert et al., 2016; van der Mispel et al.,

2017), comparison (Samendinger et al., 2018), value matching (Smith et al., 2014), and reward (Kim et al., 2018). Here, too, studies assessed various outcomes, such as PA with different measures (Friederichs et al., 2016; Kim et al., 2018; Samendinger et al., 2018; Smith et al., 2014; Zhou et al., 2018); fruit, vegetable, energy snack, and saturated fat intake (Springvloet et al., 2015); attrition (van der Mispel et al., 2017); and intervention use (van Genugten et al., 2014). They found mixed results: Kim et al. (2018) reported only positive impacts, Samendinger et al. (2018) reported no significant impacts, and Friederichs et al. (2016), Smith et al. (2014), Springvloet et al. (2015), van der Mispel et al. (2017), and Zhou et al. (2018) reported both positive and insignificant impacts. Friederichs et al. (2016) also reported that perceived competence but not intrinsic motivation, identified regulation, or perceived choice mediated the intervention effect. Van der Mispel et al. (2017) and van Genugten et al. (2014) did not test intervention impacts; rather, they focused on predicting intervention use or attrition.

Six studies (Adams et al., 2017; Alley et al., 2016; Joseph et al., 2015; Kattelmann et al., 2014; Poirier et al., 2016; Walthouwer et al., 2015) combined content, channel, and functionality personalization. They usually employed goal review (Adams et al., 2017; Alley et al., 2016; Joseph et al., 2015; Poirier et al., 2016; Walthouwer et al., 2015), recommendation matching (Alley et al., 2016; Joseph et al., 2015; Kattelmann et al., 2014; Walthouwer et al., 2015), descriptive feedback (Alley et al., 2016; Poirier et al., 2016; Walthouwer et al., 2015), evaluative feedback (Adams et al., 2017; Alley et al., 2016; Joseph et al., 2015), goal initializing (Alley et al., 2016; Kattelmann et al., 2014; Walthouwer et al., 2015), and matched timing (Adams et al., 2017; Alley et al., 2016; Kattelmann et al., 2014). In contrast, they used identification (Alley et al., 2016; Kattelmann et al., 2014), matched messenger (Poirier et al., 2016; Walthouwer et al., 2015), matched intensity (Joseph et al., 2015), and reward (Poirier et al., 2016) strategies less frequently. Assessed outcomes included various PA measures (Adams et al., 2017; Joseph et al., 2015; Kattelmann et al., 2014; Poirier et al., 2016; Walthouwer et al., 2015); engagement (Poirier et al., 2016; Walthouwer et al., 2015); satisfaction, retention, adherence, and physical and mental health (Alley et al., 2016); self-efficacy, self-regulation, and social support (Joseph et al., 2015); stress and food intake (Walthouwer et al., 2015); sleep and BMI (Walthouwer et al., 2015); and waist size (Kattelmann et al., 2014). Since each study assessed multiple outcomes, all studies in this group reported mixed (some significant and some insignificant) findings except Poirier et al. (2016), which showed positive impacts.

Only one study combined content, interface, and functionality personalization (Pyky et al., 2017) in the form of descriptive feedback, matched engagement, goal initializing, comparison, and reward. It reported improvement in life satisfaction in the intervention group, which baseline satisfaction and mood-related exercise motives moderated. The study observed no significant changes for self-rated health and other outcomes. Finally, one study (Morrison et al., 2014) employed all the four personalization types in the form of descriptive and evaluative feedback, matched engagement and timing, goal initializing, and reward. It reported disparate impacts on different health outcomes (e.g., motivation, self-efficacy, and awareness and achievement of eating and PA goals, etc.). Furthermore, adherence decreased over time (Morrison et al., 2014).

4.4.2   Specific Personalization Strategy Effects

We now examine the intervention effects for specific personalization strategies, which seven studies reported. In particular, four studies employed content personalization with only one strategy: evaluative feedback (Achterkamp et al., 2015), descriptive feedback (Hoye et al., 2015), identification (Kaptein et al., 2015), and contextualization (Li & Mao, 2015). Of these, Achterkamp et al. (2015) reported significant effects on task self-efficacy but not on task performance and self-efficacy for PA in general. Hoye et al. (2015) found positive effects on PA only at the start of the intervention period. Kaptein et al. (2015) found positive impacts on user engagement, which declined with time. LI and Mao (2015) reported that their contextualization strategy increased users' intention to reuse the application (which perceived transparency, engagement, enjoyment, and informativeness mediated) and increased social presence (which perceived engagement and enjoyment mediated).

Three studies employed a single interface personalization strategy (i.e., matching engagement) (Lepri et al., 2016; Orji et al., 2017, 2014). Lepri et al. (2016) observed improved PA when users were exposed to the application features that were matched with their personality traits. Similarly, Orji et al. (2017) reported improvements in attitude, intention to change behavior, and self-efficacy through game design as per players' personality type. Enjoyment, competence, effort, and tension mediated the effects. Last, Orji et al. (2014) found positive effects on persuasiveness by matching features/strategies to gamer types. These

studies found consistently positive results (unlike for other groups), which suggests that employing interface personalization by itself in HBC applications has good potential.

However, overall, research to evaluate and synthesize the results on personalization strategies' effects on various outcomes faces considerable challenges due to the disparate ways in which different studies have implemented the strategies (e.g., multiple ways to implement recommendation matching) and tested their effectiveness (e.g., different RCT designs). Additionally, the absence of correlation information and inconsistent predictor and outcomes measures (e.g., different measures of adherence) hinders one from conducting a meta-analysis on personalization strategy effects. In Section 5, we offer suggestions for future research to address some of these issues.

5   An Agenda for Future Research on Personalization for HBC Apps

Using the framework we propose in Figure 1 and the results from our literature review, we identified several key gaps and, thereby, issues for future research on HBC application personalization. We summarize these research directions in Figure 3 and elaborate on them below. Specifically, we discuss the research opportunities pertaining to these applications' 1) design, 2) implementation and adoption, and 3) assessment and impacts.

Design and Develop

- Identify, capture, and theorize on relevant characteristics e.g., demographic, and contextual, for personalization strategies for HBC applications
- Identify HBC personalization opportunities using new technologies e.g., AR, AI chatbots
- Examining personalization of interface and channels for HBC applications
- Develop, apply, and evaluate design theories for personalization in HBC applications

Implementation and Adoption

- Examine ways to incentivize users to share their individual characteristics, including developing and adapting privacy models for this purpose
- Understand and assess the impacts of institutional barriers and organizational contexts in the implementation of personalization in HBC applications
- Understand how to increase adherence to such personalized HBC applications, including the optimal intervention period

Assessment and Impacts

- Examine HBC and health status, in addition to other outcomes of personalization
- Examine the effects of specific personalization strategies and their combinations in a systematic manner and longitudinally
- Consider use of RCTs for assessing impacts of personalized interventions in HBC applications
- Examine the moderating and mediating effects of user/contextual characteristics on the impacts of personalization strategies

Figure 1. Key Research Problems for HBC Application Personalization

5.1   Research Opportunities Related to Design

We outline the opportunities for research on designing personalized HBC applications in terms of the user/contextual characteristics and personalization strategies (including their delivery technologies) as per our framework in Figure 1. First, researchers have employed four types of user/contextual characteristics to implement personalization (see Table 2). Among them, we found that researchers have used demographic and contextual characteristics less frequently. Thus, they may not have exploited certain individual propensities for personalized HBC interventions related to demographic characteristics (e.g., Klecun (2012) found users' education and digital literacy to impact how they used e-health, including HBC applications). Similarly, certain contextual factors that are seen to influence health behaviors e.g., availability of transport options that impacts PA (Bauman et al., 2012), would be useful to incorporate into personalization design. Additionally, other user characteristics, such as circadian preference (a personal trait) correlate with health behaviors (Schaal et al., 2010), but have yet to be exploit them for personalization. Furthermore, the reviewed studies mostly lacked theoretical foundations to help one design user and contextual characteristics for personalizing HBC applications. Thus, we suggest opportunities for future research to identify and theorize about such unused but potentially relevant characteristics for designing personalization strategies. For this purpose, researchers could also employ theories other than the ones in Table 3. For instance, they could use the social ecological model (Golden et al., 2015) to understand how to use contextual characteristics to design personalization strategies. As another example, researchers could use

the stimulus-organism-response (S-O-R) model (Mehrabian & Russell, 1974) as an overarching theory for these studies as it encompasses users' stimulus (personalization), organism (psychosocial determinants), and response (HBC and health status). We also noted that the studies we reviewed did not develop or apply design science theories (Iivari, 2020), which presents a valuable opportunity for future research.

Second, with regard to personalization strategies, future research could explore their design using advanced technologies. For instance, reward constitutes a key gamification strategy, which entails measuring users' health behavior performance and providing awards (e.g., badges) when they achieve performance targets (Zuckerman & Gal-Oz, 2014). While one study we reviewed discretely measured these behaviors (Adams et al., 2017), researchers could design awards based on real-time measurement in future. Similarly, researchers could design the comparison strategy (Samendinger et al., 2018) to be dynamic (e.g., through a real-time leaderboard design). As another example, researchers could redesign the feedforward strategy (Alamri et al., 2014; McCreless et al., 2017) whereby they predict users' future states (e.g., weight gain) based on their characteristics with advanced machine learning technologies to provide users with more effective interventions. Thus, we suggest fertile opportunities to research how one can design personalization strategies using new technologies. Another direction for future research related to personalization design stems from our review findings that researchers have used interface and channel strategies relatively less frequently than other types of personalization strategies (see Table 2). Yet, interface and channel personalization can help users in various ways, such as by reducing information overload (Jameson, 2008), which increases their satisfaction towards the system (Liang, Lai, & Ku, 2006). Thus, we call for further research on designing personalized interfaces and channels for HBC applications.

Third, in terms of personalization delivery technologies for HBC, we found that the IS/HCI studies in our review used websites and mobile apps more often (8 out of 11 studies) than messaging technologies, while we found the opposite result among the medical/health informatics studies. The difference could be due to IS/HCI researchers' interest to gain knowledge about recent and upcoming information technologies (Robey, 1996). Going forward, we call for IS/HCI researchers to continue advancing knowledge in this area by designing cutting-edge technologies for personalization delivery, such as AI assistants and chatbots, Internet of things (IoT) sensors, and augmented reality (Althoff, White, & Horvitz, 2016). Overall, the limited extent to which research has theorized about designing personalized HBC applications until now presents a huge opportunity for design science and HCI researchers to contribute to this area.

5.2   Research Opportunities Related to Implementation and Adoption

Beyond designing personalization for HBC applications, we also identified a need to examine how one can implement personalization strategies effectively. We observed that researchers have used users' demographic and contextual characteristics less frequently for personalizing HBC interventions. Researchers may not have used such characteristics much due to privacy concerns that can hinder such data collection since one can use demographic information (e.g., age) to identify individuals) (Halttu & Oinas-Kukkonen, 2017). Similarly, contextual information could be sensitive (e.g., location) or complex and dynamic (e.g., weather information) (Adomavicius & Tuzhilin, 2005). To understand and address these challenges, a useful research direction would be to explore how best to incentivize users to share their demographic and contextual characteristics for HBC intervention personalization.

With regard to implementing personalization for HBC applications, broader research questions that earlier work raised (e.g., Kelders et al., 2016) also remain largely unaddressed in the reviewed literature. These questions, such as "when should personalization and tailoring be used?" and "how should personalization in HBC applications be implemented in different contexts?", remain relevant. HBC implementations often face regulatory and institutional barriers, such as medical board approval and privacy laws (Kao & Liebovitz, 2017). Additionally, organizational contexts that two studies examined (Poirier et al., 2016; Solenhill et al., 2016) (e.g., when organizations incorporate such applications into employee health programs) could also influence their implementation. Thus, we call for research to assess and understand the impacts that these challenges and varying contexts have on HBC applications' implementation and adoption.

Last, the studies we examined experienced a similar problem: adoption and adherence to personalized HBC applications was relatively low (median of 25.6%) and typically decreased over time (e.g., Morrison et al., 2014). Hebden et al. (2014) cited this issue as a key reason for the insignificant effect that HBC interventions had on health behavior outcomes. To explain low adherence, Alley et al. (2016) suggested that personalized interventions can increase users' cognitive overload, which reduces their acceptance, because individuals are more likely to adopt interventions that they find easy to use (Carter, Corneille, Hall-Byers, Clark, & Younge, 2015). Further, the studies we reviewed implemented multiple personalization

strategies (3.03 strategies on average) in their HBC applications. Although providing personalized content to users can increase user satisfaction (Liang et al., 2006), delivering multiple interventions concurrently could induce information overload. In this regard, various studies suggested ways to increase adherence, such as to match users' preferences (Li & Mao, 2015) and provide encouragement (Kaptein et al., 2015), but these approaches did not necessarily increase adherence. Thus, we call for more research that examines how one can increase adherence to personalized HBC applications (e.g., reducing user's cognitive load). Also, at least two studies (e.g., Compernolle et al., 2015; Zhou et al., 2018) suggested that an optimal intervention period for such applications might exist. Exploring how to optimize the intervention period for different users and contexts would be another useful direction for future research.

5.3   Research Opportunities Related to Assessment and Impacts

After implementing HBC applications, researchers need to assess personalization's impacts in HBC applications using appropriate outcome measures in order to enhance their performance and evidence their effectiveness. Our review and synthesis suggest several directions for future research to evaluate impact evaluation and assess outcomes. First, both the medical/health informatics and IS/HCI studies in our review primarily focused on health-related outcomes. However, they evaluated health behavior change (HBC) levels (18 out of 21 studies) and health status (8 out of 10 studies with this outcome type) more often, while a higher proportion of IS/HCI journal papers examined psychosocial determinants (e.g., intention, attitude, self-efficacy) as outcomes (45% vs. 19%). While we need to assess such psychosocial outcomes in order to understand the theoretical mechanisms behind intervention effects, we recommend that IS/HCI studies on this topic also examine relevant HBC (e.g., increase in PA, improved diet, better sleep quality) and health status (e.g., weight, BMI, mental health) outcomes as they constitute practically relevant key outcomes.

Second, while the medical/health informatics studies in our review largely (18 out of 21 studies) examined the effects of a whole HBC application (with multiple personalized and generic strategies), the IS/HCI studies typically implemented a few personalization strategies in one study and often focused on the individual effects of specific personalization strategies (7 out of 11 studies). In doing so, researchers gained more precise knowledge about each personalization strategy. Thus, we recommend researchers continue this practice in IS/HCI research but in a more systematic manner because their findings about individual personalization strategies remain fragmented due to differing implementations and inconsistent measures. Researchers could remedy the situation by conducting HBC intervention assessment studies in which they carefully vary the individual user/contextual characteristics or the delivery technologies/modes for specific outcomes (that they would measure in a standardized way) while keeping other personalization strategy parameters constant. However, the large number of parameters and their combinations to evaluate would greatly complicate such efforts. Additionally, IS studies do not often perform longitudinal evaluations (maximum six months (McCreless et al., 2017; Pyky et al., 2017) as compared to medical/health informatics studies (up to 15 months (Kattelmann et al., 2014) in our review). In sum, we suggest that research shoulders examine the effects of specific personalization strategies and their combinations in a systematic manner and longitudinally in the future in order to better design effective HBC applications.

Third, in terms of evaluation methods, the Appendix shows that, although RCTs constitute the gold standard research method for testing HBC intervention effects, a higher proportion of medical/health informatics studies (78%) in our review adopted it than the IS/HCI studies (45%). Thus, we recommend that future IS/HCI research consider using RCTs to assess the impacts of personalized interventions in HBC applications due to the method's potential advantages in investigating cause-effect relationships while limiting bias and confounds (Reith et al., 2013). However, researchers should take care to carefully design their RCTs when doing so (Klasnja, Consolvo, & Pratt, 2011). Overall, such research will enable uncover more precise knowledge about the efficacy of personalization strategies for HBC applications.

Last, in our review, we found that user/contextual characteristics not only serve as inputs for personalization strategies but may also moderate the effect that these strategies have on various outcomes. For example, Pyky et al. (2017) used content, interface, and functionality personalization and reported improvement in life satisfaction, which baseline satisfaction and mood-related exercise motives moderated. This finding suggests fruitful directions for future research to examine the moderating effect that user/contextual characteristics have on personalization strategies' impact. Additionally, we observed that psychological states had a mediating role in some studies (Friederichs et al., 2016; Li & Mao, 2015; Orji et al., 2017), which suggests that future research could explore the mediators between personalization strategies and outcomes (see Figure 1).

6   Limitations and Conclusion

In this study, we comprehensively review and synthesize recent studies on personalizing HBC applications. However, as with any study, ours has some limitations. First, we included only peer-reviewed journal papers since peer review ensures that papers meet a certain standard and quality. Nevertheless, one can consider the studies we examined, which we sourced from comprehensively searching major databases, to largely represent mainstream research. Second, our selection criteria included studies on three main health behaviors (i.e., PA, diet, and sleep). Thus, we did not consider other behaviors, such as alcohol consumption and smoking. We leave it to future research to examine such behaviors. Third, as few studies examined the individual effects of specific personalization strategies, we lack enough data to conduct a meta-analysis to identify each strategy's effectiveness for health behavior change. Barring these limitations, we holistically overview extant research on personalization for HBC applications and suggest important directions for future research.

In particular, we identify several major gaps in the research on personalizing HBC applications. First, researchers have designed personalization based on users' demographic and contextual characteristics relatively less frequently than other characteristics. Second, research has focused little the interface and channel of delivering personalized interventions. Third, research has found typically low user adherence to personalized HBC applications with a decrease over time. Fourth, research has examined aggregate intervention effects more often than specific personalization strategies. Fifth, research has insufficiently theorized about such applications' design, implementation, adoption, and impact. We suggest that researchers have much potential to undertake design research on employing demographic and contextual characteristics for personalization and on personalization strategies that target HBC applications' interface and channel. In terms of implementation and adoption, we recommend future research to address issues such as low adherence and contextual barriers for these applications. Further, we suggest that the effects of specific personalization strategies require systematic and longitudinal investigation given that we lack cumulative evidence on their efficacy. Last, we identify a crucial need for theorization in this area for which we offer several suggestions.

Overall, with this study, we provide an integrative view of extant work and outline key directions for future research in this area. Such research can help researchers better understand users and help build effective personalization strategies for HBC applications in order to ultimately enhance health behaviors.

Acknowledgments

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Appendix: Details of Reviewed Papers

Table A1. Details of Reviewed Papers

Study	Research question(s)	Method/variables	Findings
*Achterkamp et al. (2015)	Whether feedback strategies that focus on success experience can influence self-efficacy through technology.	**Lab experiment**. IV: feedback strategy; DVs: task performance, self-efficacy for task, self-efficacy for PA in general.	Evaluative feedback: 1) task performance did not vary significantly per feedback condition but was best in the correct feedback condition and worst in the negative feedback condition. 2) The task-specific self-efficacy decreases in the negative feedback condition, while increases in the positive and correct feedback condition. 3) Feedback strategies did not have a significant effect on self-efficacy regarding PA in general.
Adams et al. (2017)	Compare adaptive vs. static goal setting and immediate vs. delayed, non-contingent financial rewards for increasing PA.	**RCT**. 2x2: goal setting (adaptive vs. static), rewards (immediate vs. delayed). DVs: step/days, moderate to vigorous PA (MVPA).	1) Participants on average increased steps/day and MVPA. 2) Steps/day and MVPA increase rank from top to bottom: Static with immediate rewards > adaptive with delayed rewards / adaptive with immediate rewards > static with delayed reward. 3) There was insufficient power to test goal x reward x intervention day interactions on rate of change post-intervention by subgroup.
*Alamri et al. (2014)	Impact that the different PA performed through a cloud-based game has on obese subjects' cognitive behavior.	**Lab experiment**. IV: PA through the game. DV: attention; relevance, confidence, satisfaction.	1) Perceived attention was the lowest compared to the other outcomes. 2) Participants reported a moderate to high levels on the relevance and confidence of components. 3) Perceived satisfaction was higher than attention.
Alley et al. (2016)	Determine feasibility and effectiveness of video-coaching session in addition to computer-tailored advice for inactive adults.	**RCT**. IV: tailoring and video-coaching vs. control. DV: PA; retention, adherence, engagement, mental health, satisfaction.	1) At nine weeks, PA increased from baseline to post intervention in all groups. The increase was significantly higher in the tailoring + video-coaching group compared with the control group. 2) No significant changes in other outcomes, except mental health scores dropped in the tailoring-only participants at post intervention.
Compernolle et al. (2015)	Effectiveness of a computer-tailored, pedometer-based PA intervention for working adults.	**RCT**. IV: computer-tailored pedometer-based intervention vs. control condition. DV: step counts; sitting, walking, PA time, attrition.	1) Daily step counts significantly increased after1 month and 3 months in the intervention group. 2) Intervention effects were significant for participants' self-reported moderate PA one month post baseline but not after three months. 3) No effects found for time spent sitting. 4) Intervention effects significant for time spent walking in at-risk sample (not reaching 10,000 steps per day at baseline) but not in the total sample.
Elbert et al. (2016)	Whether tailored health intervention via a mobile app can increase fruit and vegetable intake. Compare efficacy of text vs. auditory intervention.	**RCT**. IV: audio and text fruit and vegetable intake interventions vs. control condition. DV: fruit intake, vegetable intake, dropout rate.	1) No significant effects on fruit and vegetable intake. 2) Significant interaction between condition and perceived own health status on fruit intake but not on vegetable intake. Audio was better than others. 3) No interaction between health literacy and condition on fruit intake but significant interaction on vegetable intake. 4) Fruit/vegetable intake at pretest (sufficient vs. insufficient) moderated the above results.
Friederichs et al. (2016)	Compare Web- and SDT based tailored PA intervention (I Move) to traditional web-based tailored PA intervention (Active Plus).	**RCT**. IV: I Move, Active Plus vs. control condition. DV: PA, MVPA, perceived competence,	1) Combined intervention (I Move and Active Plus) impacted MVPA and weekly days with ≥30 min PA. 2) No differences in MVPA between I Move and Active Plus groups. 3) Active Plus group more effective than I Move group in increasing PA.

		intrinsic motivation, identified regulation, perceived choice.	4) Effects of both interventions (equally) mediated by perceived competence but not by intrinsic motivation, identified regulation, or perceived choice.
Hebden et al. (2014)	Effect of mHealth intervention (with text message, email, Internet forum) on body weight, BMI, specific life-style behaviors, and engagement with the program.	**RCT**. **IV**: mHealth tailored weight management intervention vs. control condition. **DV**: sitting time, PA, MET, food intake, engagement, weight, BMI.	1) Pre- to post-intervention, participants decreased their body weight, increased PA and reported increased vegetable and decreased sweet beverage intake 2) Differences were not significant for weight loss, BMI, self-reported PA, MET, sitting time, vegetable or fruit consumption, or sweetened beverages intake 3) Low engagement with the study materials, particularly the mobile application and Internet forums.
Hoye et al. (2015)	Effect of different levels of feedback, from minimal to use of a feedback display and coach, on PA.	**RCT**. **IV**: 4 intervention groups: minimal, pedometer, display, FTF coach. **DV**: step count; minutes of PA, MVPA, daily energy expenditure.	1) No significant group x time interaction effect for PA variables between minimal, pedometer, display groups. 2) Coaching had higher PA values throughout the intervention compared with display group. 3) Self-monitoring using pedometer resulted in more steps compared with a no-feedback condition at the start of the intervention. 4) Adding individualized coaching seems necessary to increase PA level until the end.
Joseph et al. (2015)	Effects of a multi-component, culturally-relevant intervention using Facebook and text-messaging to promote PA among African American women.	**Randomized pilot trial**. **IV**: culturally tailored e-intervention vs. non-tailored print intervention. **DV**: step count, PA frequency/ duration self-regulation, self-efficacy, satisfaction, social support.	*Between-group differences were 1) significant in decreased sedentary time, increased light-intensity and moderate-lifestyle intensity PA, 2) not significant in accelerometer measured MVPA, [and] 3) significant increases in self-reported MVPA, self-regulation for PA, and social support from family for PA.* *4) Satisfaction with the intervention was high: 100% reported PA-related knowledge gains and 100% would recommend the program to a friend.*
*Kaptein et al. (2015)	Design personalization to improve the effectiveness of persuasion. Develop design requirements for persuasion profiling system.	**RCT**. **IV**: four designs tested with cases of SMS for snacking, PA user engagement. **DV**: reduction in snacking, PA user engagement.	1) Personalization of persuasive messages directly impacted users' eating patterns in a positive and meaningful way. 2) Personalized messaging also enhanced user engagement.
Kattelmann et al. (2014)	Effectiveness of a tailored theory-based, Web intervention developed using community-based participation.	**RCT**. **IV**: tailored Web intervention vs. control condition; **DV**: food intake, PA, Sleep, BMI, weight, waist size, perceived stress.	1) No differences between experimental and control participants in BMI, weight, waist circumference, and perceived stress. 2) Small improvements in fruit and vegetable intake, vigorous PA in females, fat intake, and hours of sleep at post intervention but improvements were not maintained at follow-up.
*Kim et al. (2018)	Efficacies of three versions of a smart watch app for promoting stretching exercise.	**RCT**. **IV**: three versions: reminder, evaluative feedback, gamified. **DV**: frequency of stretch exercise	1) Reminders were effective in relaxing the mental/muscular tension of the users. 2) The motion evaluation feedback encouraged the users to stretch more. In contrast, the effectiveness of gamification was not proven.
*Lepri et al. (2016)	If personality traits interplay with the effectiveness of two social strategies for promoting PA.	**Pre-post**. **IV**: two strategies: social comparison, peer pressure. Traits: extraversion, neuroticism. **DV**: PA.	1) Extroverts exposed to a social comparison strategy were positively associated with an increase in PA. 2) They tended to decrease PA if exposed to a peer pressure intervention strategy. 3) Neurotic people tended to increase their daily PA if they are exposed to a social comparison strategy.

*Li & Mao (2015)	How does system–user communication style similarity influence the value that users perceive virtual health advisory services to have	**Online experiment**. **IV**: communication style similarity **DV**: reuse intention, transparency, enjoyment, informativeness, credibility.	1) An intelligent advisory system's communication style, when aligned well with a user's communication style, can better engage the user and lead to more perceived transparency, enjoyment, informativeness and credibility during the interaction process. 2) Overall, hedonic aspects of user perceptions are more critical for creating a feeling of social presence and reuse intentions than utilitarian ones.
*McCreless et al. (2017)	Impacts of feedback and feedforward on computer-mediated behavior change, if personality moderates impacts.	**RCT**. **IV**: feedback, feedforward. **DV**: changes in caloric intake. **Moderator**: conscientiousness.	1) Both feedforward and feedback reduce calorie consumption. 2) The intervention effect of feedforward was greater for individuals who ranked low in conscientiousness than high. 3) The interaction effect of feedforward and conscientiousness was not significant.
Morrison et al. (2014)	Whether access to POWeR tracker enhances users' goal engagement, if so, whether/how the extent of enhancement varied between participants.	**Mixed methods**. **IV**: access to POWeR Tracker app and Web-based weight management. **DV**: eating/PA goal engagement, duration, use frequency.	1) Access to POWeR Tracker showed increase in motivation, self-efficacy, awareness, and achievement of eating goals and increase in awareness of PA goals, but not in goal effort, and achievement of PA goals. 2) Participants used POWeR website for similar amounts of time when POWeR Tracker was and was not available. They mostly accessed POWeR Tracker in short bursts during convenient moments or when they considered intervention content most relevant.
*Orji et al. (2017)	If personalization in serious games for health increases effectiveness of desired intention changes. Does gamer type interact.	**Online experiment**. **IV**: personalizing serious game, gamer type. **DV**: attitude; intent to change; self-efficacy for healthy eating.	1) Achievers would respond only to reward and Conquerors would respond only to competition. 2) Tailoring game design to players' personality type improved effectiveness of game in promoting positive attitudes, intention to change behavior, and self-efficacy. 3) Evidence showed that enjoyment, competence, effort, and tension had a mediating effect.
*Orji et al. (2014)	How does the persuasiveness of 10 technology strategies vary for gamer types.	**Online survey and experiment**. **IV**: 10 persuasive technology strategies, seven gamer types. **DV**: persuasiveness, type.	1) Competition and comparison as well as self-monitoring and suggestion emerged as persuasive strategies to which most gamer types are receptive. 2) Reward and praise were positively associated with only one gamer type each. Some gamer types also perceived them both as negative.
Poirier et al. (2016)	Effectiveness of open access, Internet-based walking program that assigns daily step goals tailored to each participant.	**RCT**. **IV**: wireless activity tracker and walking program, Walkadoo vs. control condition. **DV**: daily steps, Engagement.	1) The intervention group significantly increased their steps over the control group, with treatment effects observed in sedentary and low-to-somewhat active participants alike. 2) Authors found convincing engagement levels. Participants wore their activity tracker on most days and remained active into their sixth week of treatment.
*Pyky et al. (2017)	Effects of a mobile PA intervention on life satisfaction and self-rated health among adolescent men.	**RCT**. IV: tailored mobile PA intervention vs. control condition. **DV**: PA; life satisfaction, self-rate health, weight.	1) Life satisfaction improved in intervention group. 2) Life satisfaction most likely to improve among men with low baseline satisfaction and mood-related exercise motive. 3) No significant changes in self-rated health and other DVs, but those with poor health at baseline and improved self-rated fitness during the trial were more likely to gain improvements in self-rated health.
*Samendinger et al. (2018)	Effect of mobile app using a software-generated partner (SGP) on walking motivation.	**RCT**. IV: three conditions: individual control, SGP, synchronous SGP. **DV**: walking minutes, persistence.	1) Non-statistically significant differences for mean minutes of walking between the synchronous SGP and no-partner individual control walkers. 2) Walk persistence differences by condition were positive but non-significant.
Smith et al. (2014)	Impact of ATLAS intervention for	**RCT**. **IV**: intervention vs.	1) No significant intervention effects for BMI, waist circumference, percent body fat, or PA.

	adolescent boys, an obesity prevention intervention using smartphone.	control group. **DV**: BMI, waist, body fat, screen-time, sugar-sweetened beverage intake, muscular fitness, resistance training skills.	2) Significant intervention effects for screen-time, sugar-sweetened beverage consumption, muscular fitness, and resistance training skills.
Soetens et al. (2014)	Which online tailored intervention delivery mode is more accepted and effective in increasing PA.	**RCT**. **IV**: three interventions of delivery mode: video, text, video and text. **DV**: PA, time spent on website.	1) Differences in time spent on the website were significant: video group > combination group >text group. 2) PA levels of the three groups all increased with no significant differences among groups. 3) More pronounced intervention effects among participants with low initial PA.
Solenhill et al. (2016)	Effect of tailored web-based health feedback and optional telephone coaching on health of employees in transport services.	**RCT**. **IV**: two interventions: Web, or Web and phone coaching vs. control cond. **DV**: food intake, PA, stress, sleep, BMI smoking, alcohol.	1) No significant differences in reported health habits between three groups over time. 2) Intervention groups reported higher motivation to improve dietary and PA habits compared with the control group. 3) At follow-up, intervention groups had significantly decreased motivation, whereas control group reported significantly increased motivation to change diet and PA.
Springvloet et al. (2015)	Efficacy of a cognitive, environ. feedback, web-based tailored nutrition education intervention compared to generic nutrition information.	**RCT**. **IV**: two intervention groups: individual feedback, plus environment factors. vs. control group. **DV**: fruit, vegetable, snack, saturated fat intake.	1) Both intervention versions were more effective in improving snack intake, dietary behaviors than generic nutrition information, especially in the risk groups, among both higher- and lower-educated participants. 2) For fruit intake, only the plus version was more effective than providing generic nutrition information.
van der Mispel et al. (2017)	Examine attrition patterns from an e-health intervention "MyPlan 1)0". Determine whether user characteristics predict attrition.	**Pre-post test**. **IV**: online intervention to promote PA, fruit, vegetable intake. **DV**: attrition rate across self-regulation components and user characteristics.	1) Attrition levels were higher for the fulfillment of questionnaires than for more interactive components. 2) Authors observed the highest attrition when they asked people to make their own action plan. 3) Subgroups of male users and younger adults had a lower chance to complete the intervention. 4) Younger adults were less likely to return to the website.
van Drongelen et al. (2014)	Effects of mHealth tailored advice on daylight, sleep, PA, and nutrition on pilots' health behaviors.	**RCT**. **IV**: mHealth tailored advice vs. control group, DV: fatigue, sleep, snack behavior, PA, health perceptions.	1) After six months, compared to the control group, the intervention group showed a significant improvement on fatigue, sleep quality, strenuous physical activity, and snacking behavior. 2) No significant effects for other outcome measures. 3) Low compliance.
van Genugten et al. (2014)	Which user characteristics were associated with use of online, computer-tailored intervention for weight gain prevent.	**RCT**. **IV**: user characteristics. **DV**: intervention use.	1) Number of visitors dropped over time. 2) Those with low fat intake or planning for change in PA are more likely to visit the module of behavior change plan selection. 3) Those high in restrained eating or low in proactive coping skills for weight control are more likely to revisit intervention after plan selection.
Walthouwer et al. (2015)	Is the use and effect of Web-based tailored obesity prevention intervention increased by video	**RCT**. **IV**: two delivery formats: text and video. Two conditions of delivery format preference	1) Intervention use declined rapidly over time. 2) No significant differences in use between the video and text version. 3) Intervention use was significantly higher among participants allocated to an intervention condition that

	delivery that matches users' preferred delivery format? Which demographic factors predict intervention use?	match: gender, age, education **DV**: energy intake, PA, BMI, use intention, intervention use.	matched their preferred intervention delivery format. No significant interaction terms for any outcome variables. 4) Participants with a high BMI and who felt involved and supported by the intervention were more likely to use the intervention more often. 5) Match and more intervention use did not result in better effects on BMI, energy intake, PA.
Wang et al. (2015)	Utility of a wearable device (Fitbit) and SMS text-messaging prompts to increase PA in overweight and obese adults.	**RCT**. **IV**: Fitbit tracker and app vs. Fitbit tracker, app, and SMS prompts. DVs: step counts, minutes of PA, engagement.	1) Between-group differences were significant for increased steps, fairly/very active minutes, and total active minutes. 2) The Fitbit One achieved a small increase in MVPA at follow-up and the SMS-based PA prompts were insufficient in increasing PA beyond one week. 3) More engagement in using the Fitbit tracker in the comparison group
Zhou et al. (2018)	Efficacy of mobile personalized, adaptive goal-setting intervention as compared to an active control with steady goals.	**RCT**. **IV**: personalized, adaptive goal-setting mobile app intervention vs. steady goal app. **DV**: daily steps, PA, weight, BMI.	1) Participants in the intervention group had a lower/ higher decrease in mean daily step count between run-in and 10 weeks, compared with control participants. 2) Both groups had a decrease in daily step count between run-in and 10 weeks because authors also provided interventions during run-in and collected no natural baseline. 3) No differences in PA.
Note: an asterisk before a reference denotes an IS/HCI paper.			

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