

Systematic review of context-aware digital behavior change interventions to improve health

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Abstract

Health risk behaviors are leading contributors to morbidity, premature mortality associated with chronic diseases, and escalating health costs. However, traditional interventions to change health behaviors often have modest effects, and limited applicability and scale. To better support health improvement goals across the care continuum, new approaches incorporating various smart technologies are being utilized to create more individualized digital behavior change interventions (DBCIs). The purpose of this study is to identify context-aware DBCIs that provide individualized interventions to improve health. A systematic review of published literature (2013–2020) was conducted from multiple databases and manual searches. All included DBCIs were context-aware, automated digital health technologies, whereby user input, activity, or location influenced the intervention. Included studies addressed explicit health behaviors and reported data of behavior change outcomes. Data extracted from studies included study design, type of intervention, including its functions and technologies used, behavior change techniques, and target health behavior and outcomes data. Thirty-three articles were included, comprising mobile health (mHealth) applications, Internet of Things wearables/sensors, and internet-based web applications. The most frequently adopted behavior change techniques were in the groupings of feedback and monitoring, shaping knowledge, associations, and goals and planning. Technologies used to apply these in a context-aware, automated fashion included analytic and artificial intelligence (e.g., machine learning and symbolic reasoning) methods requiring various degrees of access to data. Studies demonstrated improvements in physical activity, dietary behaviors, medication adherence, and sun protection practices. Context-aware DBCIs effectively supported behavior change to improve users' health behaviors.

Keywords

Digital behavior change interventions, mHealth, Internet of Things, Machine learning, Artificial intelligence

INTRODUCTION

Health risk behaviors, or modifiable unhealthy behaviors, are leading contributors to morbidity and premature mortality associated with chronic diseases [1]. To prevent chronic diseases, health risk behaviors, such as physical inactivity, unhealthy eating, smoking, and excessive alcohol consumption can be modified using behavior change strategies [2]. The prevalence and cost of chronic diseases attributed

Implications

Practice: Digital health interventions can positively influence health behaviors.

Policy: Policy makers, along with health care stakeholders, should formulate health policies that integrate digital health interventions into the delivery and reimbursement of health care services and the education of providers, patients, and payers.

Research: Future studies that apply advanced analytics and artificial intelligence to digital health interventions should place greater emphasis on evaluation and health impacts.

to these modifiable behaviors place a tremendous burden on health care resources. As such, public health strategies that change these health risk behaviors and lessen the rates of chronic diseases are needed.

A social-ecological approach to public health recognizes that individuals are members of the society and environments within which they live [3, 4]. Accordingly, an individual's health may be influenced by intrapersonal, interpersonal, institutional, or community factors, as well as public policy. In practice, it has been difficult for behavior change interventions to take into account the full range of social-ecological factors over time. Additionally, former studies have been cross-sectional or longitudinal with few measurement points, giving only snapshots and static views of human behavior [5].

Few health care providers are trained to deliver effective behavior change strategies for preventing or managing diseases, and significantly increasing the number of skilled providers would be costly [2]. In any case, many opportunities for supporting behavior change occur outside of the typical scenarios in which patients and providers typically interact. Fortunately, the proliferation of digital health technology, including mobile health (mHealth) applications (apps), text messaging, the Internet of Things

(IoT) (e.g., fitness wearables and ambient sensors), internet-based platforms, and health information technology exchanges, presents an opportunity to support health behavior change across a broad spectrum of settings. These technologies have improved the recording of intrapersonal, interpersonal, and environmental factors at scale (e.g., observing large populations over long and continuous periods of time) [6] and provided digital longitudinal records [7]. As a result, efforts such as the “All of Us” research program, an initiative launched by the National Institutes of Health in 2016, are able to capture longitudinal data about lifestyle, environment, and biological makeup from millions of people, including data collected from mHealth technologies [8]. Such data collection efforts are needed to mature the understanding of behavioral dynamics and the social-ecological system and to support the development of data-driven approaches in behavior interventions that leverage insights gained from such a data collection.

Digital behavior change interventions (DBCIs) employ digital health technologies for behavior modification for the maintenance and improvement of health [9]. Smartphone sensors, wearable devices, and other IoT devices connected to internet-based platforms provide opportunities to understand the dynamics of behavior through the continual collection of real-time data in an unobtrusive manner. Health behavior change research is shifting its focus to study the design and use of context-aware DBCIs that are individualized, are predictive, and provide real-time feedback.

Context-aware DBCIs have the potential to improve population health management from primary prevention efforts to the effective management of chronic diseases. Context-aware DBCIs are responsive to dynamic contextual factors that could influence the user’s behavior and tailor aspects of the intervention based on these contextual factors [10]. Importantly, in context-aware DBCIs, one should identify such “tailoring variables” (i.e., contextual factors used to decide when and how to intervene) based on evidence that the variable is useful for making intervention decisions. Measurement of the tailoring variables can be aided by digital technologies by enabling users to easily enter relevant contextual information at any time or by using a combination of sensors and algorithms to automatically infer the relevant information. For example, data from the global positioning systems and accelerometers in users’ phones are combined with algorithms for inferring the class of physical activity (e.g., sedentary, walking, and running) that is being performed and the general context for the activity (e.g., walking home from work) [11]. “Decision rules” can be used to link the tailoring variables to the available intervention options. These decisions can be triggered and executed automatically using a variety

of computational methods, including analytics and artificial intelligence (AI).

The primary objective was to identify studies using context-aware digital health technologies to automate behavior change interventions. Secondary objectives included identifying the extent to which these digital health technologies may employ analytics-based and AI-based methods for automation, the extent to which they apply known behavior change techniques [12], and their effectiveness for behavior change.

METHODS

This study was conducted in accordance with Preferred Reporting Items for Systematic reviews and Meta-Analyses (Fig. 1) [13] under an a priori protocol.

Search strategy

Included studies evaluated context-aware digital health technologies that automate behavior change interventions through analytics or AI methods, addressed clearly defined health behaviors, and reported behavior change outcomes data. MEDLINE, the Cochrane Library, and Embase databases were searched for relevant articles published in English from January 2013 to June 2020 (Supplementary Tables 1–15). Relevant conference proceedings were also screened (Supplementary Table 16), and a manual search of the bibliographies of included studies was conducted.

Screening process

One reviewer screened all titles and abstracts for eligibility against a priori established inclusion criteria (Supplementary Table 17). Studies marked for inclusion underwent full-text screening by two independent reviewers; discrepancies were resolved by adjudication or, if necessary, a third reviewer. All results at both title/abstract and full-text review stages were tracked in DistillerSR (Evidence Partners) and in EndNote.

Data extraction and quality assessment

Included studies were extracted into a structured form by one reviewer and checked for accuracy and completeness by a second. Study quality was assessed by two independent reviewers using the Oxford Levels of Evidence (Supplementary Table 18) [14]; disagreements were resolved by a third reviewer.

RESULTS

Literature searches identified 4,987 potentially relevant articles after duplicates removal. After screening, 458 citations were identified for full-text screening, of which 30 studies (reported in 33 publications) met the criteria for inclusion (Fig. 1) [11, 15–46].

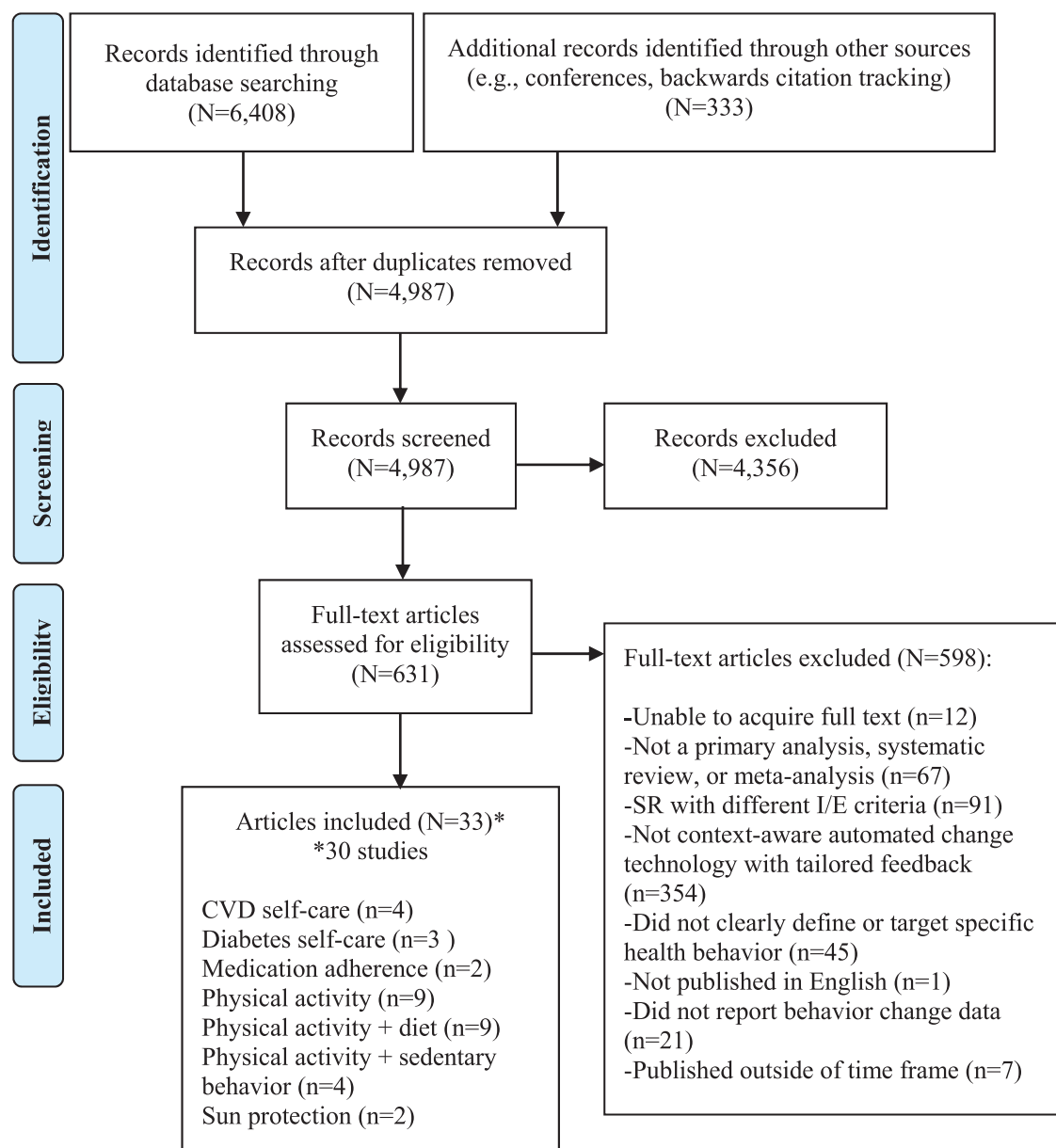


Fig 1 | Results of Literature Search, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses diagram [13]. Abbreviations: CVD cardiovascular disease; I/E inclusion/exclusion; SR systematic review.

Study characteristics

Twenty-six (79%) studies were randomized controlled trials; the remaining seven (21%) were single-arm observational studies. Most studies were conducted in the USA [11, 15–20, 22–25, 29, 31, 34, 35, 37, 38, 41, 44, 46], but 13 others were conducted in Australia [26], China [27, 28], Israel [40], Spain [30, 39], Sweden [32, 33, 36], and the Netherlands [21, 42, 43, 45]. Studies had short durations with an average follow-up of 10.9 weeks. The longest study had a duration of 52 weeks, of which 10 months were follow-up [18]. All studies were conducted in adults (59.3%, female). Participant ethnicity varied across studies. [Supplementary Table 19](#) provides study and population characterization details.

Identified DBCIs included (number of studies and percentage of included studies) mHealth apps (23, 69%), IoT wearables/sensors (22, 67%), and internet-based web applications (10, 30%; [Supplementary Table 20](#)). Analytics and AI methods required various degrees of access to data. All DBCIs leveraged an analytical component, whether it was descriptive, predictive, or prescriptive in nature. Methodologies were explicitly reported with the exception of seven studies [19, 20, 23, 24, 29, 41, 44]. An infrequent methodology identified was AI (seven studies, 21%): four mentioned machine learning (12%) [11, 29, 35, 46] and three included rules-based dialogue systems as symbolic reasoning (9%) [17, 18, 41]. [Table 1](#) defines the terms of access, analytics, and AI in more detail.

Physical activity was the most common health behavior targeted (Table 1) as the sole focus (9, 27%) [15, 16, 18, 31, 38, 42, 43, 45, 46], with dietary behavior (9, 27%) [11, 17, 20, 27–29, 39, 40], or with sedentary behavior (4, 12%) [21, 22, 34, 37]. Seven studies (21%) addressed self-care behaviors for the prevention or management of chronic diseases, including diabetes [30, 41, 44] and cardiovascular disease [26, 32, 33, 36]. The remaining four studies targeted sun protection practices [23, 24] and exclusively examined medication adherence [25, 35].

Behavior change techniques

Various behavior change techniques (Table 1) were utilized in DBCIs and were classified by groupings as per Michie et al. [12] taxonomy and ordered from most to least frequent: feedback and monitoring, shaping knowledge, associations, goals and planning, social support, reward and threat, regulation, natural consequences, comparison of behavior, repetition and substitution, comparison of outcomes, scheduled consequences, antecedents, self-belief, identity, and covert learning (Fig. 2). Behavior change techniques employed different “doses” or modes of delivery within and across the studies (e.g., fixed or changing goals). Although these techniques performed various functions, all interventions provided an educational function and all performed more than one function. These functions were categorized according to the Behaviour Change Wheel framework (Fig. 3) across the capability, opportunity, motivation, and behavior theory change model: persuasion (18 studies, 55%), education (16, 48%), enablement (15, 45%), incentivization (5, 15%), modeling (4, 12%), and environmental restructuring (4, 12%) [47, 48]. No two interventions used the same set and delivery of behavior change techniques.

Methodologies utilized in DBCIs

Analytics- and AI-based methods for enhancing DBCIs were used in association with four frequent groupings of behavior change techniques (feedback and monitoring, shaping knowledge, associations, and goals and planning; Fig. 2) and intervention functions that were primarily persuasion, education, and enablement (Fig. 3). The combination of real-time context detection and automated decision rules enables a digital intervention to provide individualized information to the user.

To evaluate the analytics- and AI-based methods used in DBCIs, the studies were organized into one or more of three descriptive categories related to technology: real-time access to data for monitoring purposes, adaptive analytics for automated feedback and recommendations, and symbolic reasoning for dialogue systems. DBCIs may collect data continuously and interact with users in real time. With real-time monitoring, users can be made aware of their behavior, if needed, in a timely manner.

Additionally, feedback and recommendations can be based on the monitored behaviors to help motivate and coach users on how to modify their goals and behaviors. Lastly, communication with the user can be facilitated by a virtual dialogue system.

Real-time monitoring was implemented in 21 studies [11, 15, 16, 21–24, 29–31, 34, 35, 37–39, 42–46] and required an appropriate level of temporal access to data to capture relevant events. These studies used behavior change techniques in the associations, shaping knowledge, natural consequences, goals and planning, and feedback and monitoring groupings within the DBCI. Ten studies of real-time monitoring as an essential component of app-based DBCIs were found to increase physical activity and/or decrease sedentary time [22, 31, 34, 37, 42], improve some sun protection practices [23, 24], and enhance medication adherence [25, 30, 35]. One medication adherence app used computer vision and machine learning via neural networks to confirm medication ingestion [35]. Two studies incorporated a wearable device with a digitally enhanced behavior change strategy to monitor health data as a key component of the intervention; it integrated a glucose sensor with a specially designed mobile app to target self-care behaviors addressing glucose variability [30, 44]. The adaptive goal-setting interventions mentioned above relied on the supplementary technique of real-time monitoring by the participant and/or by the use of IoT devices (e.g., wearable devices) to obtain data needed for setting new goals [11, 15, 16, 21, 22, 25, 29–31, 34, 37–39, 42, 43, 45, 46].

Twenty-two studies (reported in 24 articles) provided adaptive feedback and recommendations with a subgroup utilizing adaptive goal setting [11, 15, 16, 21, 22, 25–34, 36–40, 42, 43, 45, 46]. Six of the above real-time monitoring studies used adaptive goal setting to improve physical activity and/or dietary behavior [11, 15, 16, 29, 38, 46]. These studies used behavior change techniques in the goals and planning, feedback and monitoring, and shaping knowledge groupings in the DBCIs. Of these, three used machine learning, designed to progressively improve its performance over time, to produce tailored, adaptive goals and recommendations based on the real-world behaviors of the participants [11, 29, 46]. The other three studies relied upon simpler, analytics-based approaches (e.g., rank-order percentile) to generate adaptive daily goals [15, 16, 38]. These algorithms required continuous and repeated measurement of physical activity behavior and used the data to create new goals based on the past activity of the user. Additionally, these simpler analytics-based DBCIs added reward and threat, associations, and/or scheduled consequences behavior change techniques to the intervention for adaptive goal setting. Using pre-post comparisons, the authors reported improvements in

Table 1 | Summary of findings

Author, year; level of evidence ^a	<i>n</i>	Target health behavior	Behavior change technique groupings ^b	Intervention functions ^c	Data and technology segments ^d
Adams, 2013 [16]; 1b	20	Physical activity	1–5, 7, 10, 14	Education, persuasion, incentivization	Access, analytics
Adams, 2017 [15]; 2b	96	Physical activity	1–2, 4, 7, 10	Education, persuasion, incentivization	Access, analytics
Bickmore, Silliman, 2013 [18]; 2b	263	Physical activity	1–4, 7	Education, persuasion, enablement, modeling	Access, analytics, AI
Bickmore, Schulman, 2013 [17]; 2b	122	Physical activity, fruit and vegetable consumption	1–5	Education, persuasion	Access, analytics, AI
Block, 2015, 2016 [19,20]; 1b	339	Physical activity, dietary behavior	1–4, 7, 10, 14	Education, enablement	Access, analytics
Boerema, 2019 [21]; 4	15 ^e	Physical activity, sedentary behavior	1–2, 4, 7–8, 12	Education, enablement, environmental restructuring, persuasion	Access, analytics
Bond, 2014 [22]; 2b	30	Physical activity, sedentary behavior	1–2, 5, 7, 10	Education, enablement, environmental restructuring, incentivization	Access, analytics
Buller, 2015 [24]; 2b	202 ^e	Sun protection practices	2, 4–5, 7	Education, persuasion	Access, analytics
Buller, 2015 [23]; 2b	604	Sun protection practices	2, 4–5, 7	Education, persuasion	Access, analytics
Chandler, 2019 [25]; 1b	54	Medication adherence for hypertension	1–4, 6–7, 10	Education, enablement, incentivization, modeling, persuasion	Access, analytics
Coorey, 2019 [26]; 1b	397	Cardiovascular disease management and prevention	2–4, 6–7, 10, 11	Education, enablement, incentivization, persuasion	Access, analytics
Duan, 2017 [28]; 2b	493	Physical activity, fruit and vegetable consumption	1–4, 6, 8–9	Education, enablement, modeling, persuasion	Access, analytics
Duan, 2018 [27]; 1b	136 ^e	Physical activity, fruit and vegetable consumption	1–4, 6, 8–9	Education, enablement, modeling, persuasion	Access, analytics
Fico, 2020 [30]; 4	20	Diabetes management and prevention	2, 4, 6–7, 9, 11–12	Education, enablement, environmental restructuring, persuasion	Access, analytics
Finklestein, 2015 [31]; 2b	27	Physical activity, sedentary behavior	1–2, 4, 7	Education, enablement, environmental restructuring	Access, analytics
Everett, 2018 [29]; 2b	55	Physical activity, dietary behavior	1–2, 4, 7, 10	Education, enablement, modeling	Access, analytics, AI
Hovland-Tänneryd, 2019 [32,33,36]; 2b	172	Cardiovascular disease (heart failure) prevention and management	2, 4, 7, 11	Education, enablement, persuasion	Access, analytics
King, 2016 [34]; 1b	95 ^e	Physical activity, sedentary behavior	1–4, 6–8, 10–12, 14	Education, enablement, incentivization, modeling, persuasion	Access, analytics
Labovitz, 2017 [35]; 1b	28	Adherence to anticoagulation therapy	1–2, 7, 11	Education, enablement	Access, analytics, AI
Naimark, 2015 [40]; 1b	99 ^e	Physical activity, dietary behavior	1–2, 4, 6–7, 11	Education, enablement, persuasion	Access, analytics
Pellegrini, 2015 [37]; 4	9 ^e	Physical activity, sedentary behavior	1–2, 7	Education, persuasion	Access, analytics
Poirier, 2016 [38]; 2b	265	Physical activity	1–3, 7, 10	Education, incentivization, persuasion	Access, analytics
Rabbi, 2015 [11]; 2b	17	Physical activity, dietary behavior	1–2, 4, 7, 8	Education, persuasion	Access, analytics, AI

(Continued)

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Table 1 | Continued

Author, year; level of evidence ^a	<i>n</i>	Target health behavior	Behavior change technique groupings ^b	Intervention functions ^c	Data and technology segments ^d
Recio-Rodríguez, 2016 [39]; 1b	833	Physical activity, dietary behavior (Mediterranean diet)	1–2, 4, 7	Education, enablement, persuasion, training	Access, analytics
Stein, 2017 [41]; 4	159 ^e	Diabetes prevention and management	1–5, 11, 15	Education, enablement, modeling,	Access, analytics, AI
Tabak, 2013a [43]; 1b	30	Physical activity	1–4, 7	Education, enablement, persuasion	Access, analytics
Tabak, 2013b [42]; 1b	34 ^e	Physical activity	1–4, 7	Education, enablement, persuasion	Access, analytics
Toschi, 2018 [44]; 2b	30	Self-care behaviors on glucose variability	1–2, 4, 7, 11	Education, enablement, persuasion, modeling	Access, analytics
van Dantzig, 2018 [45]; 1b	70	Physical activity	1–2, 4, 7–8, 10	Education, enablement, incentivization	Access, analytics
Zhou, 2018 [46]; 1b	64	Physical activity	1–2, 7	Education, persuasion	Access, analytics, AI

AI artificial intelligence; RCT randomized controlled trial.

^aAssessed using Oxford Levels of Evidence (more information in Supplementary Table 15) [14]: 1b, RCT, prospective cohort study with good follow-up; 2b, retrospective cohort study, or poor follow-up RCT; 4, case series or superseded reference standards.

^bGroupings of behavior change techniques: 1, goals and planning; 2, feedback and monitoring; 3, social support; 4, shaping knowledge; 5, natural consequences; 6, comparison of behavior; 7, associations; 8, repetition and substitution; 9, comparison of outcomes; 10, reward and threat; 11, regulation; 12, antecedents; 13, identity; 14, scheduled consequences; 15, self-belief; 16, covert learning (according to Appendix 2, Table 19 of Michie et al. [12]).

^cFunctions defined in Michie et al. [47].

^dSegments regards access to data (static and dynamic; transactional and summary; sources of data [e.g., social media, sensors and wearables, electronic health records, surveys, and mobile]); *analytics* regards descriptive, predictive, or prescriptive methods, for example: visualization, mining, and reporting of data; simulation; regression analysis; causal inference; and optimization. Artificial intelligence regards machine learning (e.g., natural language processing, neural networking or deep learning) and symbolic reasoning (e.g., expert systems).

^eBoerema et al. [21], only 14 participants data used; Buller et al. [23], only 193 completed posttest survey; Duan et al. [27], only 83 participants analyzed; King et al. [34], only 89 participants analyzed; Naimark et al. [40], only 85 participants completed the study; Stein et al. [41], only 70 active users were available for analysis; Tabak et al. [42], only 15 participants in the intervention arm are reported. See Supplementary Fig. 1 for more information.

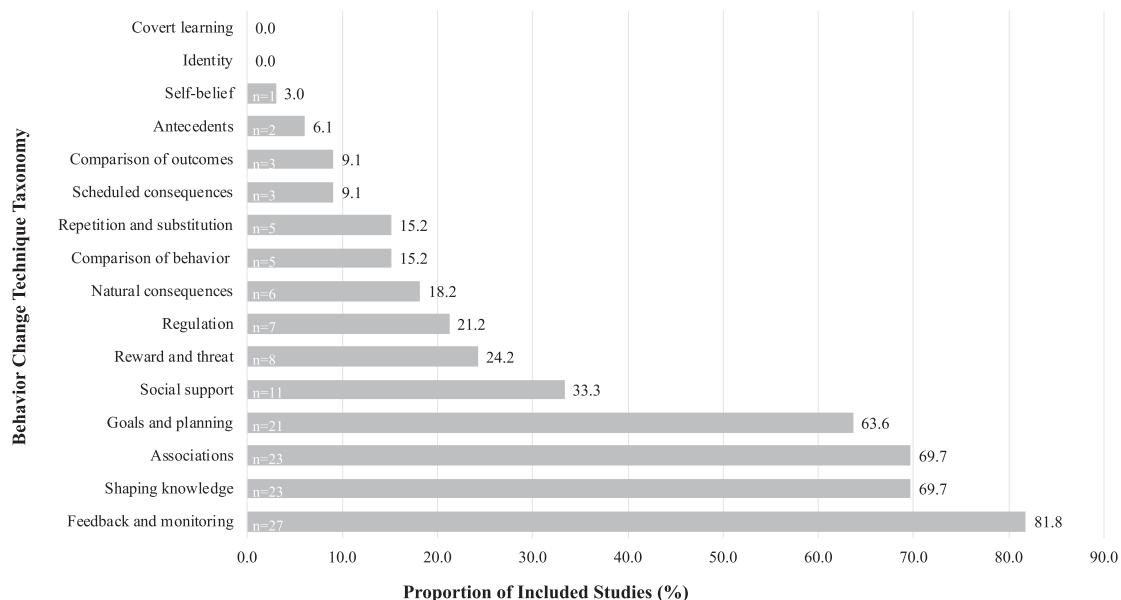


Fig 2 | Frequency of behavior change techniques by their groupings utilized in the included studies. This bar graph denotes the proportion (%) of hierarchically clustered behavior change techniques identified in the 33 included studies according to groupings and taxonomy outlined by Michie et al. [12]. Frequency number provided in bar as *n* = X.

physical activity (e.g., increased number of steps or weight loss or less sedentary behavior) and dietary behavior (e.g., decreased caloric intake and/or increased fruit and vegetable consumption).

Four studies (reported in five articles) used symbolic reasoning-based dialogue systems as a mode of interacting with users [17–20, 41]. All dialogue systems used behavior change techniques within

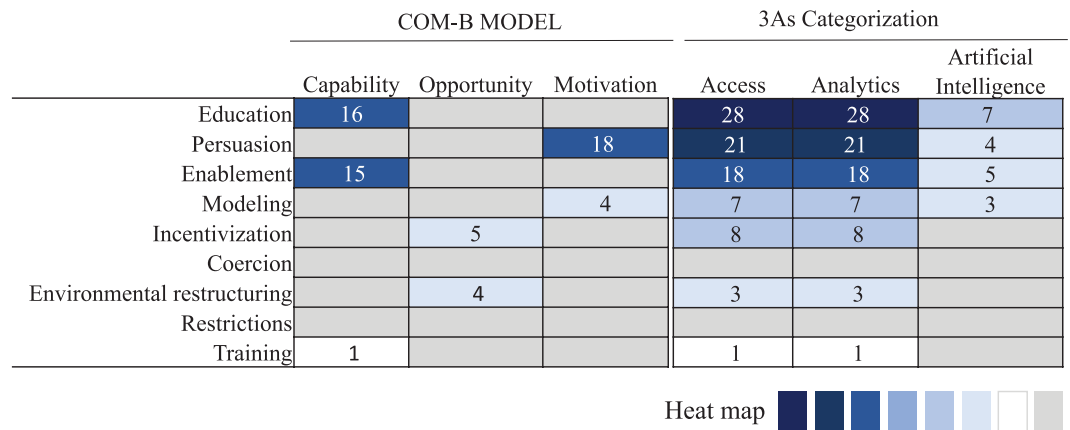


Fig 3 | Frequency distribution of intervention functions adopted across capabilities, opportunities, and motivation behavior-based theory of change model and Access, Analytics, and Artificial Intelligence (3As categorization) data and technology segments. Color indicates intensity of use across the included studies (high use, dark; low use, light; and no use, gray) and the number in each box indicates the frequency of each intervention function identified. Data and technology segments defined and mapped to included studies in [Table 1](#).

the shaping knowledge grouping in their DBCIs. Dialogue systems, also known as conversational agents, are autonomous and intelligent software entities that are virtually represented for communication with a user. While some of the studies used embodied conversational agents (ECAs) [17, 18], others used simpler interfaces (e.g., simple chatbot interface [41] or interactive voice response [19, 20]). Only two studies explicitly stated that the dialogue system was a rules-based form of symbolic reasoning [17, 18], and the others did not specify if an AI-based methodology was used. No trends could be identified regarding the observed changes in various target behaviors across these studies with the use of a dialogue system.

Assessing efficacy with direct comparisons could not be done due to the heterogeneity in interventions and comparators across studies. In addition, even when studies assessed the same target behavior (e.g., physical activity or exercise), the studies used different measures for the outcomes (e.g., predicted mean steps/day and active minutes/day) or reported findings as between-group differences with different comparisons from study to study.

Health outcomes

Despite multiple chronic diseases (e.g., chronic obstructive pulmonary disease, cardiovascular disease, including coronary artery disease and heart failure, diabetes, prediabetes, obesity, and stroke) being targeted, few studies reported associated changes in health (e.g., limited to clinical and intermediate) outcomes following DBCIs. Weight loss was most commonly reported; weight loss varied, with a range of mean weight loss (1.44–3 kg) reported across six studies [17, 19, 29, 40, 41, 44]. Three studies in prediabetic or diabetic patients reported a range of decreased

hemoglobin A1c (HbA1c) (–0.5% to –0.1%) at endpoint as a measure of glucose control [19, 29, 44]. After 6 months, a culturally tailored mHealth program to monitor medication adherence and manage Hispanic hypertension resulted in controlled systolic blood pressure (<140 mmHg) [25]. Only one study noted extensive results on health outcomes [29]. In 6 months, compared with the control group, the intervention group achieved both clinically and statistically significantly greater mean reductions in fasting glucose, HbA1c, and body weight. Reductions in body mass index, waist circumference, and triglycerides/high-density lipoproteins were also significantly greater in the intervention group compared with the control group.

Study quality

Based on Oxford Levels of Evidence [14], 16 trials provided Level 1b evidence [16, 19, 20, 25–27, 32, 34–36, 39, 40, 42, 43, 45, 46]; 13 studies were assessed as Level 2b [11, 15, 17, 18, 22–24, 28, 29, 31, 33, 38, 44]; and 4 observational studies provided Level 4 evidence [21, 30, 37, 41]. Reasons for downgrading study quality included selection bias, high loss to follow-up, and lack of intent-to-treat analysis. The long-term effects of the DBCIs could not be assessed due to the relatively short duration of the included studies. [Table 1](#) provides the level of evidence assessment for individual studies.

DISCUSSION

This systematic review identified 30 studies (33 publications), investigating interventions that utilized mHealth applications, IoT devices, and/or internet-based platforms to improve health behavior outcomes to deliver context-aware, automated DBCIs. All DBCIs provided automated feedback

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based on the dynamic and individualized context of the user. DBCI methodologies were generally underdescribed by authors. Common intervention functions included persuasion, education, and enablement to provide communication to induce feelings to stimulate action, increase knowledge or understanding, and reduce barriers to increase capability for change, respectively [48]. Within these interventions, the frequent behavior change technique groupings included feedback and monitoring, shaping knowledge, associations, and goals and planning to primarily increase physical activity for weight loss and/or promote healthy diets and enhance disease prevention and/or self-management behaviors. Only one DBCI met our inclusion criteria to examine an aspect of smoking cessation [26], but none examined alcohol behavior modification, which is amongst the top contributors to modifiable mortality and morbidity [49]. These behaviors should be targeted by context-aware DBCIs as they impose significant economic and utilization burdens on the health care system.

Advantages of context-aware DBCIs

Based on the evidence, an integral design component for context-aware DBCIs includes immediate feedback based upon the user's real-world behavior. Requiring a "human" physician, counselor, or coach to deliver this type of feedback is not feasible or possible in practice. However, context-aware DBCIs that continuously analyze data, acquired both passively from sensors and actively from user input entered into mobile apps, can overcome the limitations of cost, scale, and responsiveness that are often associated with human-delivered interventions.

The data suggest that context-aware DBCIs can be supplemented by analytics- and AI-based methodologies to improve user individualization of interventions. For instance, the behavior change technique of goal setting can be made adaptive via algorithms that make dynamic goal recommendations based on the users' behavioral data [11, 15, 16, 29, 38, 46]. Only four studies applied machine learning, a subset of AI algorithms designed to improve their own performance over time, to positively impact outcomes [11, 29, 35, 46]. However, algorithms can automatically detect relevant events from sensor data, reducing the burden of self-reporting, and provide users with an awareness of their behavior and/or health risk. For example, context-aware DBCIs were used to track and inform users of behaviors, such as medication ingestion [35], prevention of sunburns [23], and glucose management [44]. Finally, communication of health information by shaping knowledge can be more accessible using AI-enabled ECAs and other conversational agents (e.g., chatbots), which provide a more "natural" interface for implementing virtual coaching/counseling [17, 18, 41], and personalized advice [11, 23].

Opportunities for advanced analytics and AI in digital health technologies

Explicit analytic methods in DBCIs to drive behavior change were identified in this systematic review. Moreover, AI in the form of machine learning effectively facilitated behavior change to positively impact both health behavior and clinical outcomes [11, 29, 35, 46]. Machine learning algorithms can create behavioral profiles of end users derived from the raw data obtained from wearables (e.g., physical trackers) or sensors via their smartphones as part of the IoT. Device interconnection by the IoT creates new data sources that can be leveraged and analyzed. There is potential for these methods to glean insights from these new data sources to influence real-time behavior change by generating personalized feedback, promoting user awareness, and providing context for recommendations [11, 29]. Figure 4 describes approaches for best practices to leverage access to data, analytics, and AI for the improvement and sustainability of health outcomes when designing DBCIs.

During the screening process, only 5% of DBCIs screened for eligibility met our inclusion criteria. Most excluded studies lacked context awareness, whereby automated interventions were not informed by user input, activity, or location. Other excluded studies did not target a specific health behavior for their intervention. Furthermore, some studies only reported health outcomes rather than specific behavioral outcomes (e.g., pre-post DBCI behavior change data) resulting from their intervention. Despite many promising studies providing DBCIs, particularly from the engineering community, often the evaluations focused on implementation outcomes (e.g., usability) rather than behavior change. Cross-functional teams should work together in the future to design appropriate interventions and behavior evaluation studies.

Use of dialogue systems to enhance communication in digital health technologies

Automated dialogue systems using symbolic reasoning to mimic human interaction were used in several of the studied DBCIs [17–20, 41]. Two studies (three reports) were of DBCIs that used software agents [17, 18, 41], including AI-enabled ECAs using avatars [17, 18], to bolster motivational interviewing (MI) and thereby promote behavior change. These virtual anthropomorphic representations were capable of limited conversations with the human user using both verbal and nonverbal (e.g., body language) communication in a multi-modal interface. ECA-based avatar 3D computer graphics in dialogue systems have wide acceptance by their users and can demonstrate empathy, a key part of MI [50]. Users in ECA-based interventions have reportedly favored the computer interviewer to human counselors in some cases [51]; the

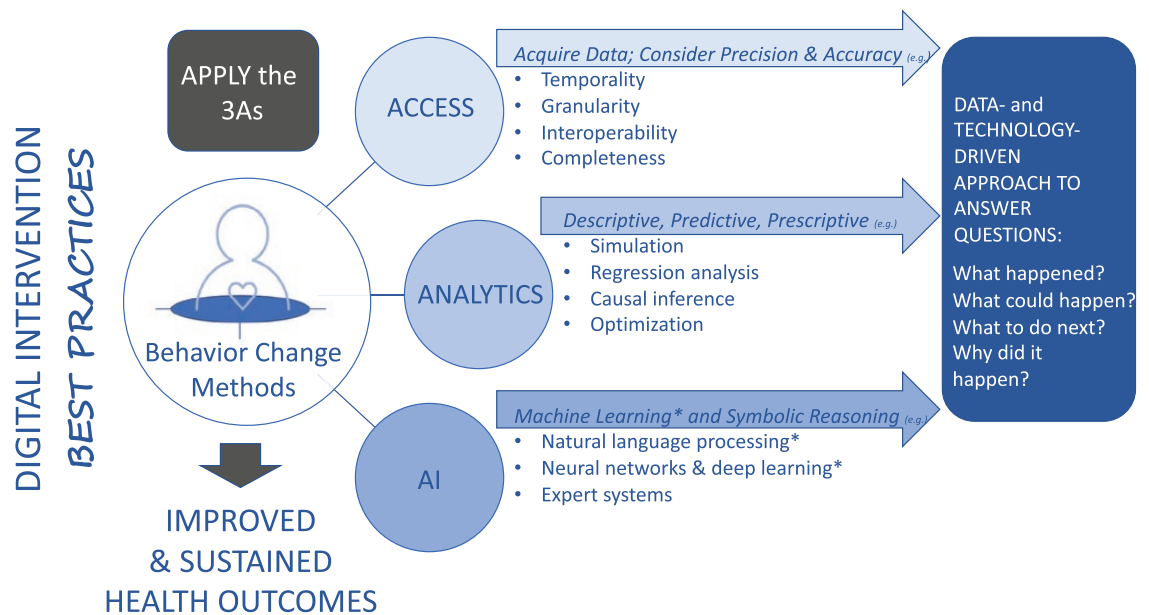


Fig 4 | Description of data and technology segments—the 3As—best practices for digital interventions. Recommendations for digital behavior change interventions include the leverage of the 3As (access, analytics, and artificial intelligence [AI]), which combines data- and technology-driven approaches to improve and sustain health outcomes. Access regards the acquisition of data and consideration of the precision and clarity of data sources, such as their temporality (i.e., frequency of refreshing and/or updating), granularity (e.g., individual- versus population-level data and geographic context), interoperability (i.e., how data sources can be aggregated), and completeness (i.e., gaps in what was expected to be collected vs. actual collection). Additional considerations may include the level of data transparency and consumer-mediated data exchange, which may be related to blockchain and other key technologies. Analytics is a broad classification of applied mathematics that analyzes acquired data and draws conclusions based on that information. Categories of analytics include descriptive (e.g., data summarization of historical trends), predictive (e.g., techniques to infer trends), and prescriptive (e.g., specification of actions that can be taken to meet relevant objectives) analytics. AI includes methods that are designed to emulate various aspects of human intelligence, including the ability to learn and/or reason. AI may be separated into two categories: machine learning and symbolic reasoning. Machine learning is the method of data analysis that makes decisions with limited human intervention after the system learns from the data and identified patterns; it includes the methods of natural language processing and simple or complex (e.g., deep learning) neural network modeling. Implementation of symbolic reasoning methods follow logical rules to produce new knowledge in expert systems, such as rules-based dialogue systems.

subjects did not fear embarrassment nor judgment, more easily reported risky behaviors (e.g., excessive drinking and unsafe sex), and fewer barriers for counseling exist with a computer interviewer. Using automated dialogue systems is consistent with the perspective that simulated face-to-face conversations make DBCIs more accessible to individuals who have low reading or functional health literacy [52].

Clinical integration of DBCIs

Consumer-based DBCIs can be integrated into clinical practice settings. Two medication adherence studies noted the integration of health care provider monitoring with the intervention [25, 35]. These DBCIs were supported by oversight from the clinical care team to ensure that proper messaging was transmitted to the patient when a noncompliance event was automatically detected. In this case, because of the potential immediate health impact of medication nonadherence, an appropriate degree of involvement of the provider was important for ensuring patient safety and necessary follow-up, if required. Additionally, three studies provided risk score or risk estimates for cardiovascular disease [26,

33] and hypertension [25]; of these, one study examined an electronic health (eHealth) application that was integrated into select parts of a primary care eHealth record.

Policy implications of context-aware DBCIs for public health Advances in mHealth and the ubiquity of smart devices, including phones and tablets, and other personal tracking devices provide consumers with greater autonomy in managing their health. Additionally, policy review has surmised that mHealth platforms will be more effective than other eHealth platforms because of increased mobile phone utilization [53], and the uptake and usage of smartphones is unprecedented in low-, middle-, and high-income countries [54]. For example, the Be He@lthy, Be Mobile joint initiative run by the World Health Organization and the International Telecommunication Union is advancing attention to mHealth services globally, including innovation in the areas of AI and wearables to support public health [55]. As such, public health organizations will be essential to enable the creation and maintenance of infrastructure and services for mHealth platforms.

The policy also cautiously recommends large-scale deployment of digital health technologies with the advisement to consider the effects of the digital divide, whereby disparities may be exacerbated in vulnerable populations where individuals lack mobile phones and/or internet access or where literacy for health and/or technology is limited [56]. In support of this advisement, the DBCIs identified in this review required internet access, and literacy of technology was typically not assessed. ECAs were well received amongst users and promoted increased and more open communication of health information by its users. Technologies that support more “human-like” interactions could potentially help address some concerns regarding technology literacy.

Finally, real-time monitoring for disease management (e.g., glucose management, blood pressure control, and medication ingestion) was identified with positive impacts on health behaviors. Recently, pharmacy benefit managers (PBMs) have evolved to support a standalone digital health formulary (e.g., Express Scripts and Caremark) to integrate DBCIs into public health practices [57, 58]. These value-based PBMs are being designed to reduce barriers and improve medication adherence for chronic diseases. Additionally, the provision of appropriate reimbursements, incentives, and education to practitioners can help promote such a cultural shift. User engagement with DBCIs will also be an important consideration. As such, researchers should continue to confirm the identification of safe, effective, and scalable interventions with real-time supportive components using evidence-based approaches.

Strengths and limitations

This systematic review has several strengths. First, this is a novel review. Many systematic reviews have been conducted to evaluate the effectiveness of mHealth and eHealth interventions in improving health; however, no previous reviews to our knowledge have focused specifically on context-aware DBCIs to provide individualized interventions to the user. Second, an exhaustive literature search was conducted, including gray literature evaluation that prioritized sensitivity over specificity. Third, the limited evidence from the subset of literature identified gaps in adequately designed and reported studies to examine context-aware DBCIs; limited collaboration and integration exists between the domains of public health, behavioral science, computer science, and health care.

Our results should be interpreted in the context of a few limitations [59]. The findings are of limited generalizability due to the relatively small number of identified studies, most of which were of moderate study quality and performed in the USA. Quality limitations included study sample sizes lacking power and diversity and insufficient follow-up durations to assess long-term changes in health-related outcomes.

The interventions were heterogenous; they used multicomponent interventions that combined a number of different techniques, which minimizes the possibility of valid head-to-head comparisons of the efficacy of the interventions across studies. Lack of complete reporting regarding interventions and methodologies are additional limitations. These issues make it difficult to isolate the component (or particular combination of components) associated with intervention effects [59]. Another limitation stems from the nature of measuring and reporting the types of outcomes measured in these studies. Baseline assessments were poorly performed or not well characterized. Additionally, some studies relied entirely on participant reporting (particularly for dietary behavior outcomes), which is not always reliable and may be biased. However, for some outcomes, patient (or participant) report is the only reasonable way to measure the outcome. Future studies should use validated instruments for collecting outcome data and, when possible, include associated objectively measured health outcomes. Furthermore, many DBCIs exist on the market but were not eligible for our study due to their general lack of peer-review. Therefore, the included studies are not necessarily a reflection of the state-of-the-art for DBCIs, but the available evidence regarding the effectiveness of context-aware DBCIs is limited at this point in time.

CONCLUSIONS

Context-aware DBCIs can positively influence health behaviors. Many DBCIs utilized a combination of analytics- and AI-based methods to automatically tailor interventions based on contextual feedback, even if small in scope and scale. Opportunity exists to build on this foundation and assess DBCIs with deeper use of analytics, greater utilization of contextual data for personalization, and larger population scale.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Translational Behavioral Medicine* online.

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Compliance with Ethical Standards

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Ethical Approval: This article does not contain any studies with human participants performed by any of the authors. This article does not contain any studies with animals performed by any of the authors.

Informed Consent: This study does not involve human participants and informed consent was, therefore, not required.

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