Mobile Health for the Self-Management of Chronic Diseases:

A Systematic Review of Tool Characteristics, Usage, and Health-Related Effects

Abstract

Background: Mobile health (mHealth) creates opportunities to improve chronic disease self-management. Yet, we lack evidence on mHealth characteristics and use patterns associated with effectiveness.

Objective: Our systematic review seeks to (1) deliver a systematization of mHealth across the mobile media ecosystem and (2) capture the status quo of research from usage to health-related effects.

Methods: We searched five databases for mHealth studies on diabetes and chronic lung diseases. Narrative syntheses and effectivity assessments (cross-tabs) were applied.

Results: We reviewed 101 studies. Research prioritizes health-related effects, with actual mHealth use playing a subordinate role. Smartphone-based self-tracking apps and cell phone-based SMS were most prevalent. Basic systems were successful in enhancing cognitive, behavioral, and clinical outcomes, while more advanced systems frequently improved patients' mental states. Theory is underused and inexplicit. Associations between use and health-related outcomes are inconclusive.

Conclusions: Current research is equivocal regarding mHealth characteristics and use patterns associated with effectiveness.

Keywords

mHealth, mobile Health, self-management, chronic diseases, systematic review

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Due to the aging population, steady increase in unhealthy lifestyle habits, and growing exposure to air pollution, chronic diseases now dominate the disease spectrum in industrialized countries, thus posing a serious threat to public health (RKI, 2020). Globally, the most prevalent chronic diseases include the metabolic disorders type 1 and type 2 diabetes and the respiratory diseases asthma and chronic obstructive pulmonary disease (COPD; WHO, 2022). Given this detrimental trend and recognizing the inevitable shortcomings in the healthcare system, the World Health Organization (WHO, 2003) claims that the encouragement of self-management efforts among patients with chronic diseases “may have a far greater impact on the health of the population than any improvement in specific medical treatments” (p. 21).

Thereby, chronic disease management requires more than just medical care. Indeed, day-to-day self-management comprises three areas of responsibility: 1) the *acquisition of knowledge* about one’s condition and its treatment, 2) *behavioral management*, including both *medical adherence* and *condition management* in terms of a healthy diet and physical activity, and 3) *emotional management* for maintaining psychosocial well-being (Clark et al., 1991; Corbin & Strauss, 1985). To educate patients about generic and disease-specific self-management tasks, healthcare providers traditionally recommend structured training programs – so-called self-management programs (Lennon et al., 2013). In their brevity and didactic structure, however, traditional self-management programs fall short in addressing the individual needs and emotional burdens experienced by patients living with chronic diseases (for a review, see Nolte & Osborne, 2013). Moreover, the transition from supervised self-management programs to self-guided management at home is often poorly executed, leaving patients feeling overwhelmed (Boland et al., 2018). As a result, levels of patient empowerment remain low (e.g., Daruwalla et al., 2019) and rates of non-adherence high (e.g., the magnitude of medical non-adherence for various chronic diseases ranges between 40%-65%; Llorca et al., 2021).

Aided by the proliferation and ubiquity of mobile media, mHealth gives reason to rethink the traditional self-management approach. By accompanying patients through the day and afforded by adaptive, responsive, and interactive features, mHealth provides readily accessible and tailored information, reduces communication barriers with healthcare providers, and helps with continuous monitoring of health parameters (Rossmann & Krömer, 2016). Hence, mHealth is poised to transform self-management practices and sustain disease awareness, adherence, clinical parameters, and overall well-being. Although a plethora of evidence syntheses initially convey a promising picture of improved health outcomes following mHealth use (for evidence syntheses across chronic diseases: Cucciniello et al., 2021; Fan & Zhao, 2022; Hamine et al., 2015; diabetes: Kitsiou et al., 2017; Whittemore et al., 2020; asthma: Farzandipour et al., 2017; Hui et al., 2017; Song et al., 2022; COPD: Alwashmi et al., 2016; Yang et al., 2018), a closer look reveals that mHealth research is still in its infancy, marked by notorious theoretical underdevelopment and methodological weaknesses (e.g., Chib & Lin, 2018). Moreover, when considering behavioral (e.g., adherence), cognitive (e.g., self-efficacy), or emotional outcomes (e.g., distress), results are far more scattered (e.g., Song et al., 2022; Wang et al., 2017).

Yet, even most evidence syntheses lack a holistic view by focusing on the effects of single tools, especially smartphone apps. Thereby, we also miss crucial insights into mHealth use, its drivers, and associations with health outcomes, which might account for the inconclusive picture in effect studies (Kohl et al., 2013). Recent studies examining the use of mHealth for chronic disease self-management show that patients make use of the entire mobile media ecosystem instead of relying on just one specific self-management app (e.g., Rossmann et al., 2019). Thus, by focusing on single mHealth systems, extant reviews overlook the wide spectrum of mobile self-management solutions available to and used by patients. In addition, mHealth tools vary with regard to features and attributes offered. However, little research put forward a systematic tool characterization of mHealth, thus resulting in a black box that masks the effectiveness of different technologies (Duplaga & Tupek, 2018). Consequently, our understanding of mHealth is fragmented and lacks evidence on mHealth characteristics and use patterns associated with effectiveness. This systematic review aims to address these shortcomings by integrating studies on uses and effects and considering mHealth systems within the entire mobile media ecosystem. With this, we contribute to a more in-depth understanding of mHealth in the context of chronic disease self-management and to an advanced systematization mHealth characteristics.

Desideratum I: The Need for a Comprehensive Systematization of mHealth

Mobile health is a rapidly expanding market encompassing an ever-evolving portfolio of technologies with multifaceted functionalities reaching far beyond disease-specific smartphone apps. In the diabetes context, for instance, patients may monitor their blood glucose levels with the help of a glucometer and a designated self-tracking app, and seek support on (non-disease-related) social media on their smartphones (e.g., Rossmann et al., 2019). Attempts to systemize characteristics relevant to mHealth have been made in the form of app quality scales, which help to identify potentially relevant tool characteristics (e.g., Anderson et al., 2016; Devan et al., 2019; Stoyanov et al., 2015). For instance, the App Chronic Disease Checklist (Anderson et al., 2016) categorizes app characteristics into engagement (e.g., gamification, customization, interactivity), information management (e.g., statistics, privacy and data security, information quantity and quality), functionality (e.g., feedback, intuitive design, connection to services), and ease of use (e.g., usability, automation, reminders). Despite specifying relevant attributes and sharing many commonalities, the scales lack sufficiency and discriminative validity. Furthermore, they focus on apps only. Also, previous literature reviews characterizing mHealth either have a limited view on smartphone apps (Farzandipour et al., 2017; Hui et al., 2017) or do not sufficiently differentiate between the variety of tool characteristics within mHealth systems (Qin et al., 2022; Song et al., 2022). Consequently, also the relationship between various tool characteristics of mHealth and their effectiveness has not yet been thoroughly explored, making it difficult to interpret current evidence comprehensively and pinpoint the most effective mHealth solution for the purpose at hand. Currently, the only certainty seems to be that multi-feature apps show more encouraging results than single-feature apps (e.g., Farzandipour et al., 2017; Hui et al., 2017).

Hence, there is an urgent need for an advanced and exhaustive systematization of tool characteristics of mHealth that scales up to the entire mobile media ecosystem. This review seeks to step inside the black box by systematically and rigorously summarizing tool characteristics of mHealth, according to five dimensions, comprising the envisaged self-management tasks and media characteristics reaching from the outermost layer—the hardware—to their internal ingredients—the intervention contents:

1) As outlined above, self-management tasks comprise knowledge management, medical management, condition management, and emotional management (Clark et al., 1991; Corbin & Strauss, 1984), which are to be supported by the use of mHealth.

2) Mobile health systems run on a range of *mobile device*s, from basic cell phones to more sophisticated smart devices, including smartphones, tablets, and wearables such as fitness trackers and smartwatches (Brew-Sam, 2019). Even more, self-management might rely on additional devices and medical meters (e.g., glucometers for diabetes management, peak flow meters for asthma/COPD management; Rossmann et al., 2019).

3) Thereby, mHealth is accessed on various *platforms* embedded within mobile devices. In addition to native voice telephony and short message services (SMS), today's digital landscape affords self-management via websites, apps, and other platforms already used outside of self-management, i.e., multimedia message services (MMS) and social media (Abroms et al., 2012; Ruco et al., 2021). Moreover, platforms vary in their degree of interactivity, from one-way push-media that reach out to users, two-way push-media that require users to respond, to interactive pull-media that users actively use on their own initiative (Brew-Sam, 2019).

4) *Media attributes* refer to the constituent interfaces of mHealth platforms. These can be broadly categorized into communication hubs for exchanges between patients and their support

network (van Rensburg et al., 2016), self-tracking features to record, store, and analyze health data (Lomborg et al., 2018), resource materials as the digital pendant to traditional self-management programs (Novak et al., 2013), and notifications that pop up on the lock screen, irrespective of whether the user is currently using the device (Danaher et al., 2015).

5) Beyond these technological properties, mHealth solutions feature specific strategies to promote, encourage, and sustain health behavior – the so-called *behavior change techniques* (BCTs). BCTs are the smallest "active ingredients within interventions" (Michie et al., 2013, p. 23), intended to trigger behavior. Common BCTs in mHealth systems include feedback, prompts, or goal setting features for specific health behaviors (Middleweerd et al., 2014).

Desideratum II: The Need for a Holistic Investigation of mHealth

The emergence of new health technologies raises questions as to whether patients adopt these innovations in the first place and how they integrate them into their self-management routine (Ammenwerth et al., 2019). Hence, to fully grasp effect mechanisms, we must look beyond tool characteristics and deal with the temporal flow of mHealth use from initial adoption or rejection decisions, to post-adoptive satisfaction evaluations, and patterns of continued use (Karnowski, 2020). Only then will it be feasible to establish a link between usage and health-related outcomes—the significance of which has been amply demonstrated by previous studies on mHealth for physical activity (Reifegerste & Karnowski, 2020; Stehr et al., 2020) and breastfeeding (Sawalha & Karnowski, 2022). However, according to previous reviews on mHealth for chronic diseases, the bulk of primary studies jumped straight into the examination of health-related effects of mHealth and omitted crucial research on patients' actual uptake of mHealth (Hui et al., 2017; Kohl et al., 2013).

In addition to considering mHealth use, drawing on established theories of health behavior is an important prerequisite to strengthen the effectiveness of interventions (Riley et al., 2011). The recourse to theoretically sound predictors, i.e., behavioral determinants, helps researchers analyze and comprehend where differences on the inter- and intra-individual level in mHealth use and effects come from (Brew-Sam & Chib, 2020; Chib & Lin, 2018). However, it appears that the practical implementation of mHealth has outpaced the theoretical foundation of the field (e.g., Brew-Sam, 2019). A first step in narrowing the gap between practice and research is to apply theory to the design of mHealth interventions, that is, to address and integrate relevant theoretically proposed predictors in mHealth systems (e.g., Riley et al., 2011). Thereby, integrating theory in mHealth designs can be achieved by incorporating appropriately selected BCTs derived from behavior change theories (e.g., Direito et al., 2018). Previous reviews on mHealth (e.g., Middelweerd et al., 2014; Riley et al., 2011) and electronic health (eHealth; e.g., Webb et al., 2010) repeatedly found strong support for the use of theory in digital health design elements to enhance intervention outcomes (see also Rossmann, 2015; Stehr et al., 2022; Glanz & Bishop, 2010). However, a recently conducted meta-analysis on mHealth for physical activity found that the use of theory did not moderate weight loss (Qin et al., 2022). With only six out of 24 studies referring to a behavior theory, however, this finding might be attributable to the sparse occurrence of theory.

In addition, the study of mHealth as a research field involving technology use for personal health, demands an integrated theoretical approach (Ammenwerth, 2019). For one, this includes theories on new media use regarding dichotomous (post-)adoption decisions and continued use (Karnowski, 2020). Secondly, (mobile) self-management, as a health behavior, also requires the consideration of cognitive and motivational predictors as proposed in various (health) behavior models (Lippke et al., 2021). Ultimately, for a holistic investigation of mHealth, research must integrate usage and effects and enrich these dimensions with theory-based behavioral determinants to gain a complete picture of the whole process of mHealth use.

Review-guiding Framework

Recognizing the complexity of tackling mHealth in its entirety, from inherent tool characteristics, to underlying theories and behavioral determinants, and (mobile) self-management outcomes, calls for a comprehensive framework. To this end, we utilize the O_1-S-O_2-R model by

McLeod, Kosicki, and McLeod (1994). This communication mediation model, which originated in the field of political and mass media communication, lends itself to the study of health and mobile media communication (e.g., Namkoong et al., 2017). For the purposes of our review, the model provides a comprehensive framework to systematically and seamlessly trace mHealth use from *preexposure orientations* (O_1; theories and determinants of mHealth use), the use of the mHealth *stimulus* (S; theories of mHealth design, tool characteristics, and actual mHealth use), subsequent *postexposure orientations* ($O_{2;}$ theories and determinants of health-related effects), down to the health-related outcome *response* (R; health-related effects of mHealth use). Figure 1 details the O_1-S-O_2-R model in the context of mHealth.

Objectives and Research Questions

Following the desiderata and review-guiding framework laid out above, the objectives of our systematic review are to (1) deliver an advanced and exhaustive classification of tool characteristics of mHealth that spans the entire mobile media ecosystem and (2) capture the status quo of research on the whole process of mobile self-management from usage to health-related effects. WAlong the O_1-S-O_2-R model, we derive our specific research questions:

RQ1: What are the overall results in terms of a) mHealth use and b) health-related effects?

RQ2: What are the tool characteristics of mHealth in terms of a) envisaged self-management tasks, b) devices, c) platforms, d) media attributes, and e) BCTs?

RQ3: How do different tool characteristics of mHealth influence a) mHealth use and b) health-related outcomes?

RQ4: What theory base (if any) guides the design of mHealth interventions, the evaluation of mHealth use, and the evaluation of health-related outcomes?

RQ5: How does the use of theory influence a) mHealth use and b) health-related outcomes?

RQ6: How are mHealth use and health-related outcomes related?

Method

We conducted a systematic review of the literature in line with the Cochrane Handbook (Higgins et al., 2020) and the PRISMA Statement (Page et al., 2021). An a priori registration of the review was performed on PROSPERO (ID: CRD42022337284). Extracted data, supplementary materials, and additional evaluations are openly accessible from the study's OSF repository (https://osf.io/sg7tw/?view_only=4e90c83695ae44adb099b5f923efbb27).[1]

Inclusion and Exclusion Criteria

We developed the eligibility criteria based on the PICOS framework (population, intervention, comparator, outcome, study design; Schardt et al., 2007) considering the following aspects (Table 1): The study *population* includes patients of all age groups diagnosed with type 1 diabetes, type 2 diabetes, asthma, or COPD as main users of mHealth. This scope reduces the risk of overgeneralizing findings for one disease or age group or overlooking generally valid findings across diseases and age groups. To achieve an advanced systematization of tool characteristics of mHealth, it is essential to consider *interventions* across the mobile media ecosystem. Therefore, the only criterion for inclusion is that the object of investigation are health interventions on a mobile device. Hence, stationary devices are not part of this review. *Comparators* may receive no, traditional, offline, or non-mobile digital interventions. Yet, the presence of a comparator is not a decisive prerequisite for inclusion, as both quantitative interventional and observational *study designs* are eligible—with the latter usually not including a comparator. *Outcomes* of interest include the tool characteristics of mHealth, employed theory base, and outcomes measured regarding mHealth use and health-related effects.

Search Strategy

Accounting for the interdisciplinary field of mHealth, a disciplinary diverse search strategy was employed. Thus, electronic databases centered around communication (CMMC), psychology (PsycInfo), medicine (Medline), and computer sciences (ACM) were consulted. ACM also

[1] Due to page limitations, we included additional evaluations in the supplementary materials. These include an assessment of the methodological quality of the study corpus using the Mixed-Methods Appraisal Tool (Hong et al., 2018) and health-related effectivity assessments by age group and type of disease.

includes conference proceedings, which tend to be published faster than journal articles and thus reflect current trends in research more accurately. Google Scholar covers a broad field of disciplines and provides a valuable source for locating non-English records and grey literature (e.g., unpublished manuscripts and preprints), which mitigates the risk of language and publication bias. Thus, the first five hit pages of Google Scholar were searched as well.

The search string is identical for each database and consists of pertinent terms for the topic blocks “mHealth”, “chronic disease”, and “self-management” (see PROSPERO). Terms within a block are linked by the Boolean operator ‘OR’; terms from different blocks by ‘AND’. Two-part terms are enclosed in quotation marks for an exact match; truncations at the end of the root word act as placeholders for extensions. Searches were restricted to abstracts and records published in English and German from 2010 onwards.

Screening and Selection of Eligible Studies

The search strategy was applied on June 14, 2022 and produced 3,097 records, which we stored on the reference management software Endnote and from there onto Rayyan, a web-based screening software. Duplicates were automatically identified, manually checked, and deleted (n = 408). After that, the first author screened titles and abstracts of the 2,689 records for compliance with the inclusion criteria. In this step, 2,356 records were excluded. Then, full texts for the remaining 333 papers were retrieved, read, and once again compared against the inclusion and exclusion criteria. During this process, we excluded 232 papers, leaving 101 papers up for review. Uncertainties during study selection were discussed and resolved between both authors. The search process is detailed in the PRISMA 2020 flowchart (Figure 2).

Data Extraction and Coding Scheme

Data extraction started on June 22, 2022 and was documented in an excel spreadsheet (OSF) using a combination of closed numeric codes. The coding frame covers basic bibliographical and methodological study information. Further codes for the elements of mHealth research were derived from the O_1-S-O_2-R framework (Figure 1). The initial codes are based on our scoping searches made in advance. Nonetheless, codes for systematic reviews are developed in an iterative process by supplementing inductive codes according to the study material (Fleeman & Dundar, 2017), leaving room for exploratory insights. To identify BCTs (*RQ1e*), we referred to the well-established BCT Taxonomy (BCTTv1) by Michie et al. (2013), which provides a nomenclature of 93 lower-order BCTs, organized into 16 higher-order BCTs. For example, the higher-order BCT “social support” comprises “unspecified social support”, “practical social support”, and “emotional social support” in lower-order. To ensure correct use of the taxonomy, we used the official app “BCTs” (23LDT, 2017), which contains definitions, coding instructions, and examples for every BCT. However, since the BCTTv1 was originally created for the development and description of traditional offline interventions, new BCTs will likely emerge within the innovative field of mHealth that will lead to necessary extensions and refinements.

Effectivity assessments (*RQ1*, *RQ3*, *RQ5*) were performed as follows (cf. Stehr et al., 2022): If at least one measurement of the respective outcome type resulted in a statistically significant positive effect, we coded it with “1”. Accordingly, code “0” indicates no or significant negative effect. Depending on the study design, a significant effect may be a statistically significant between-group or within-group difference or significant relation between mHealth and the respective outcome. The rating for each study refers to the last follow-up measurement. A *p*-value of ≤0.05 or – if not stated by *p*-value – confidence intervals excluding “0” were defined as statistically significant. Overall effectiveness for each study was determined on a summary of the codes for every outcome type measured: If none of the outcomes were positively influenced, code “0” indicates that the intervention was ineffective overall. Code “1” implies the case of mixed results, i.e., if only some of the outcome types were positive. Finally, code “2” indicates overall effectivity with positive effects on all outcome types measured. Coding of all 101 was performed in two runs by the first author. Uncertainties during coding were consulted and discussed with the second author, until agreement was reached.

Data Synthesis Techniques

Data were synthesized in a narrative form accompanied by tables displaying absolute and relative frequencies of categories (Ryan, 2019). First, overall study characteristics and main findings of each study were aggregated (Table A.1, OSF). Frequencies of variables of interest were examined in a narrative and tabular form. Associations between elements of mHealth research and the studies' effectiveness were investigated by means of cross-tabs.

Quality Assessment Tools

The quality of the study corpus was appraised using the *mobile health evidence reporting and assessment checklist* (mERA; Agarwal et al., 2016). This checklist allows to critically appraise the quality and generalizability of mHealth interventions along 16 items covering content, contextual, and technical implementation of mHealth (Agarwal et al., 2016). Results are presented in tabular form with the occurrence rate of the criteria fulfilled.

Results

Characteristics of the Study Corpus

Bibliographic Information[2]

All 101 papers are published in English-language journals. Of the five databases searched, only papers retrieved via Medline (92/101, 91.1%) and PsycInfo (9/101, 8.9%) entered the sample. Thus, contributions from medicine and nursing sciences (66/101, 65.35%), followed by health sciences (18/101, 17.8%) predominate, while computer sciences (9/101, 8.9%), psychology (2/101, 2.0%), sociology, and communication science (1/101, 1.0% each) are weakly represented. Most first authors are affiliated with US universities or organizations (29/101, 28.7%). Publication years range from 2011 and 2022, with about half of the articles published between 2020 and the first half of 2022 (47/101, 46.5%), indicating that the research interest in mobile self-management proliferated in recent years.

Methodological Information

[2] Bibliographic information refers to papers, not studies.

Randomized controlled trials (51/101, 50.5%) and single-arm pre-post studies (34/101, 33.7%) are the most common study designs. Nine studies are non-randomized controlled trials (8.9%). Seven studies are cross-sectional (6.9%), two of which were interventional with post-only measurements, two of which asked participants about a mHealth solution already in use, and three of which stayed within the general topic of mHealth. Interventional studies (n = 96) were scheduled for an average of 22 weeks (*Min* = 2, *Max* = 104, *Mdn* = 24). After baseline, most studies followed up once (59/96, 61.5%). The sample size across all studies amounts to 33,756 participants (*Min* = 9, *Max* = 12,530, *M* = 334.2; *Mdn* = 73). In studies with a comparator (n = 64), the sample size in mHealth groups sums up to 5,065 (*Min* = 9, *Max* = 899, *M* = 79.1, *Mdn* = 43) and in comparator groups to 5,273 (*Min* = 7, *Max* = 900, *M* = 82.4, *Mdn* = 43.5) participants. Most participants were recruited in the US (27/101, 26.7%). On average, participants were 47 years old (*Min* = 12.3, *Max* = 69.8, *Mdn* = 51.5, 12 of 101 n/a).

The majority of the studies dealt with diabetes (80/101, 79.2%). More specifically, most studies focused on type 2 diabetes (45/101, 44.5%), followed by studies on both types (15/101, 14.9%), type 1 diabetes (14/101, 13.9%), and a few studies not specifying the type of diabetes (6/101, 5.9%). Proportionally, fewer studies dealt with the respiratory diseases (21/101, 20.8%), asthma (11/101, 10.9%), and COPD (10/101, 9.9%). The distribution of the age groups by type of disease corresponds to the prevalence (Table A.2, OSF).

Quality of the Study Corpus

Quality ratings for the 101 included studies according to the mERA checklist can be found in Table 2. On average, the studies fulfilled 7.5 out of 16 criteria of the mERA checklist (46.7%, *Mdn* = 8, *Min* = 2, *Max* = 13). Only a minority of studies reported mHealth quality criteria such as infrastructure, cost assessment, data security, contextual adaptability, and interoperability ($n \leq 30$ each). But even more fundamental specifications regarding the technology, delivery, and content of employed mHealth systems were missing in about one-third of studies ($n \leq 69$ each).

Outcomes of Interest

As shown in Table 3, almost one in three studies only assessed health-related effects (28/101, 27.7%). Fourteen studies dealt exclusively with mHealth use (14/101, 14%). Yet most studies took both perspectives into account (59/101, 58.5%).

mHealth use. Table 3 also specifies the types of outcomes in the 73 studies considering mHealth use. Due to the forced-exposure design in the majority of studies, *adoption* decisions remain largely unconsidered (25/73, 34.3%) and were mainly assessed by the retention rate after enrolment. *Post-adoption* was evaluated more frequently, with almost half of the studies asking patients on their satisfaction with mHealth (46/73, 63.0%). Forty-four studies (60.3%) assessed *continued use*, which was mostly obtained automatically, i.e., by tracking the login frequency to different mHealth features over time.

Health-related effects. Health-related outcome measures can be grouped into five types (Table 4): 1) *Cognitive* outcomes were analyzed in every second study (42/87, 48.3%) with most studies testing patients' disease-specific knowledge (20/87, 27.6%) or asking them to assess their level of self-efficacy (24/87, 22.9%). Other cognitive values, i.e., perceived benefits, perceived barriers, perceived severity, illness beliefs, and confidence in healthcare were measured less frequently ($n < 4$ each). 2) *Behavioral* outcomes were measured in more than two-thirds of studies (62/87, 71.3%). Most studies assessed self-management behaviors overall (36/87, 41.4%), while some studies examined medical adherence (24/87, 28.7%) and dietary, physical, or smoking behaviors (n < 8 each) specifically. About one in five studies recorded unplanned healthcare visits and hospitalizations as a certain illness behavior (16/87, 18.4 %). 3) *Emotional* outcomes (18/87, 20.7%) such as distress/depression (14/87, 16.1%) and perceived social support (7/87, 8.1%) were the least addressed outcome type. 4) *Quality of life*, a specific outcome type capturing both mental and physical well-being, was assessed in more than a quarter of the studies (25/87, 28.5%). 5) *Clinical* outcomes were measured in most studies (68/87, 78.2%). Most studies relied on laboratory (e.g., HbA1c levels, FEV1 airflow) and metabolic (e.g., weight, BMI) parameters (62/87, 71.3%) or self-report measures of health status (e.g., asthma/COPD control; 9/87, 10.3%). Most effect studies examined two types of outcomes (32/87, 36.8%; M = 2.49, Mdn = 2, *range* = 1-5).

Answering the Research Questions

Overall Results (*RQ1*)

Answering *RQ1*, we provide an unfiltered overview of the statistical evidence on mHealth use and health-related effects. Seventy-one of the 73 use studies (71/73, 97.3%) provided descriptive data, while only two studies performed statistical procedures with regard to post-adoptive satisfaction differences between the mHealth and control group. While one study found higher satisfaction in the mHealth group, the other study found that the mHealth and control group were equally satisfied with the intervention. Since two studies alone do not warrant an effectivity assessment, answering our research questions regarding the influence of different tool characteristics (*RQ3a*) and theory (*RQ5a*) on mHealth use is not feasible.[3]

Almost all effect studies analyzed effects statistically (83/87, 95.4%). About three in five studies reported significant improvements in cognitive (24/40, 60.0%), behavioral (38/59, 64.4%), and clinical outcomes (41/67, 61.2%). To a lesser extent, emotional outcomes (6/18, 33.3%) and quality of life (43.5%) were positively influenced by mHealth. Ultimately, almost half of the studies reported overall significant positive effects (39/83, 47.0%). The share of mixed (31/83, 37.4%) and ineffective studies (13/83, 15.7%) was considerably lower.

Characteristics of mHealth Solutions *(RQ2)*[4] and Their Effectiveness *(RQ3b)*

[3] In an effort not to omit the dimension of mHealth use, Table A.1 (OSF) documents the descriptive insights on adoption, post-adoption, and continued use.
[4] Here, the reference value corresponds to studies that addressed a specific mHealth solution (n = 98).

To systemize the prevalence of tool characteristics in studied mHealth solutions (*RQ2*) and their health-related effectiveness (*RQ3b*), we structured our results according to the previously introduced dimensions (also see figure 3, summarizing the insights of *RQ2*):

Envisaged self-management tasks. Almost all interventions aimed to support patients' medical management (90/98, 91.8%). Likewise, knowledge (80/98, 81.6%) and condition management (75/98, 76.5%) received a fair share of attention. In contrast, emotional management was somewhat neglected (42/98, 42.3%). Table 5 shows that, fittingly, positive cognitive effects were strongly supported through mHealth for knowledge management. Interestingly, mHealth for emotional management was successful in influencing behaviors but rather failed on the emotional level. Quality of life improved mainly through mHealth for conditional and emotional management. Clinical benefits were comparable across self-management tasks.

Mobile devices. More than half of mHealth services were smartphone-based (56/98, 57.1%). Basic cell phones were employed in every fifth study (20/98, 20.4%). Only three studies used tablets exclusively (3/98, 3.1 %). Six studies left the decision between a smartphone or a tablet (4/98, 4.1%) or a smartphone or a cell phone (2/98, 2.0%) open. Thirteen studies gave no indication of the hardware used, but judging from the platform, eight interventions required at least a cell phone (8/98, 8.2%) and five studies at least a smart device (5/98, 5.1%). Almost half of mHealth services required additional equipment (44/98, 44.9%). All but two of these (i.e., activity tracker; indoor air quality monitor; 2/44, 4.6% each) were medical instruments (i.e., glucometer, 29/44, 65.9%; glucose sensor, 4/44, 9.1%; pulse oximeter, 5/44, 11.4%; peak flow meter, 4/44, 9.1%; inhaler adapter, 2/44, 4.6%; spirometer, forehead thermometer, 1/48, 2.3% each). Mostly, external devices were connected to the main device via Bluetooth (22/44, 50.0%). Otherwise, patients were required to transfer data manually (16/44, 45.4%) or by a plug (2/44, 4.6%; 4 of 44 n/a).

Of note, cell phones scored more positive effects on cognitive, behavioral, and clinical levels, while smart devices were more successful in improving emotions and quality of life

(Table 6). Regarding the mode of data transfer, there is a slight tendency in favor of manual operations. However, case numbers are too scattered to permit a fair comparison.

Platforms. In line with the supremacy of smart devices, apps were the most employed platform (57/98, 58.2 %). Next up in order were SMS (29/98, 29.6%). Other platforms, including websites, MMS (5/98, 5.1% each), social media, and voice telephony (1/98, 1.0% each) were less common. Alongside main platforms, supplementary delivery channels were added in 18 studies (18/98, 18.4%). Most mHealth systems constitute interactive pull-media (66/98, 67.4%). Of the remaining 32 push-media (32/98, 32.7%), more than half were unidirectional (17/32, 53.1%). All apps, websites, and social media interventions were interactive, while only one SMS intervention allowed patients to initiate contact. MMS are spread across the spectrum of interactivity (Table A.3, OSF).

Mirroring the device-associated effectiveness shown above, Table 7 reveals that SMS interventions exhibited the most promising results overall, particularly on the cognitive, behavioral, and clinical levels. In contrast, app-based studies were more successful in treating emotions and quality of life. As other platforms contribute less to the research base, their effectiveness remains indistinct. Except for outcomes on the clinical level, multi-platform strategies seem relatively ineffective. In terms of the degree of interactivity, a now familiar pattern emerges: While push-media, especially bidirectional, excelled on the cognitive, behavioral, and clinical levels, they did not achieve favorable results on emotional outcomes. Among studies employing interactive pull-media, however, about half showed positive significant effects per outcome type, i.e., also on the emotional level.

Media Attributes. Eighteen media attributes were allocated across 98 mHealth solutions. Instead of listing them disjointedly, they are grouped according to their archetype:

1) Regarding *communication* features (66/98, 67.4%), a distinction must be made between communication with *real co-users* (58/98, 59.1%), i.e., healthcare providers (48/58, 82.8%), peers within the mHealth network (12/58, 20.7%), informal caregivers (9/58, 15.5%),

study authors (7/59, 12.7%), and artificial intelligence-based entities in the form of *chatbots* (5/98, 5.1%) and *embodied virtual personal assistants* simulating health consultants (1/98, 1.0%). Communication portals were mostly *private chats* (29/98, 29.6%) or system-bound (in-app) voice or video *calls* (12/98, 28.6%) which opened the dialog between one patient and another co-user. In *public forums*, many-to-many exchange between peer patients or coordinated one-to-many addresses from healthcare providers to patients occurred (12/98, 12.2%).

2) About two-thirds of mHealth services offered *self-tracking* features (64/98, 65.3%). Data collection was performed automatically (supported by motion detection or external equipment) or manually by user input and comprised numeric indicators and open diary entries. On call, the system played back accumulated data series through visualization, statistics, or plain texts. To assist self-tracking, some studies added special features: In three instances, patients used the mobile's *camera* (3/98, 3.1%) to document meals or physical complications (e.g., foot ulcers). To involve patients' support network, some mHealth services generated *smart visit reports* that transmit self-tracked data to co-users (18/98, 18.4%). Other systems offered built-in directories such as *databases* (8/98, 8.2%) to check the nutritional contents of food items and GPS-enabled *maps* (3/98, 3.1%) to check the surrounding air quality.

3) Slightly more than half of mHealth services worked with automated *notifications* (50/98, 51.0%) that popped up (audibly) on the device's lock screen. Although the notifications were clickable, the included information has often been kept short enough so that users could read everything directly from the thumbnail without having to unlock device.

4) *Resources* (43/98, 43.9%) in mHealth (apart from texts in notifications and chat messages) were mainly provided in *written* form (33/98, 33.7%) and were sometimes complemented by *images* (7/98, 7.1%) or *gifs* (1/98, 1.0%). *Audio*-only files were not frequently employed (2/98, 2.0%). One-fifth of mHealth services provided *videos* (19/98, 19.4%). Where evident, videos were animations or pre-recorded films created by healthcare staff. In general, resources contained disease-related and medical information or instructions on operating

external equipment. Once made available, patients could access and consult these resources as needed. Seldom resources appeared in the form of mobile games, in which users played through exemplary scenarios to get a hold of educational materials (2/98, 2.0%).

The mean number of individual media attributes per system was 3.4 (*Mdn* = 3, *range* = 1-9), with most systems comprising media attributes from two archetypes (33/98, 33.7%). Mapping media attributes to platforms shows that almost all media attributes are represented in apps, while other platforms – in line with their more restricted technological properties – hold a more limited array of media attributes (Table A.4, OSF). Nonetheless, even some SMS interventions contained self-tracking features, usually found in apps. Moreover, MMS interventions did not necessarily fulfill the purpose of communication but provided a platform for unidirectional dissemination of multimedia resources.

Interestingly, the rate for overall and clinical effectiveness was highest for the media attribute that is the most straightforward in scope and operation: notifications (Table 8). Although routinely used, self-tracking was the least effective feature, especially on the behavioral level. Given that self-tracking inherently requires users to perform self-management tasks, this finding is surprising. Improvements in cognitions were best supported by mHealth containing communication features, particularly private chats. With regard to co-users, the highest rate of overall effects was achieved when informal caregivers were involved (Table A.5, OSF). Resources were also successful in improving cognitive outcomes, although this was more likely to be achieved through audio-visual than written content. All in all, the results were more positive for single-feature than for multi-feature systems. However, there is a lack of sufficient data on emotional outcomes and quality of life to make a clear assessment.

Behavior Change Techniques. Fourteen higher-order BCTs (all except for *repetition and substitution* and *identity*) were present within the 98 mHealth solutions examined. Of the remaining 81 BCTs in lower-order, 42 were never used. Although the 39 original BCTs achieved to capture the majority of active ingredients within mHealth, the BCTTv1 in its current form was not entirely sufficient. Therefore, six further BCTs were defined inductively: *tailoring*, *alerts signaling critical condition*, *test of knowledge*, *performance ranking*, *gamification*, and *inspirational simulation.* Table 9 contains their assignment to a higher-order category, definition, and application example.

Each mHealth system contained at least one and a maximum of 21 BCTs, producing a mean of 9.9 BCTs (*Mdn* = 10). *Pharmacological support* (90/98, 91.8%; higher-order: *regulation;* 90/98, 91.8%) and *instruction on how to perform a behavior* (80/98, 81.6%; higher-order: *shaping knowledge;* 80/98, 81.6%) accounted for most common BCTs. Three-quarters of systems were tailored to fit the patient, their disease status, and treatment plan (75/98, 76.5%). In more than two-thirds of mHealth solutions, behavior change ought to be stimulated by *goal setting (behavior)* (69/98, 70.4%; higher-order: *goals and planning*; 72/98, 73.5%) and *prompts/cues* (66/98, 67.4%; higher-order: *associations*, 68/98, 69.4%). Moreover, the BCTs *feedback on behavior* and *self-monitoring of behavior* were fairly strongly represented (64/98, 65.3% each; higher order: feedback and monitoring, 64/98, 65.3%). *Information about health consequences* of beneficial or detrimental health behaviors are included in about one-third of mHealth services (33/98, 34.0%; higher-order: *natural consequences*, 34/98, 34.7%), and so is *unspecified social support* (32/98, 32.7%; higher-order: *social* support, 61/98, 62.2%). The remaining BCTs were integrated less frequently.[5] The mapping of higher-order BCTs to the archetypes of media attributes reveals that some active ingredients are inherently rooted in certain media attributes (Table A.7, OSF): As such, feedback and monitoring are tied to self-tracking (64/64, 100.0%), while, naturally, social support is found in almost all communication systems (60/66, 90.9%). Nearly all notifications contained prompts as calls to action (42/50, 84.0%), and resources were used to shape knowledge (41/43, 95.4%).

[5] A detailed enumeration of all 45 BCTs can be found in Table A.6 (OSF).

A look into the last column of Table 10 indicates that no BCTs proved particularly effective overall. At the very least, more frequently applied BCTs (i.e., regulation, shaping knowledge, goals and planning, feedback and monitoring) ranked relatively equal and comparatively high in their overall effectiveness. Strikingly, mHealth systems that aimed to trigger behavior change with rewards or affirmative statements on self-belief were the least effective overall. On the cognitive level, the most efficacious mHealth interventions were those educating patients about natural consequences of their behavior and those providing social support. Positive effects on behavior frequently occurred when patients were made aware of antecedents of their behavior or were offered behavioral comparisons. Assisting patients to set goals also improved behavior change to a similar level. Regarding emotional outcomes, none of the BCTs stood out as particularly effective, not even social support or self-belief. Apart from natural consequences, quality of life improved most often when patients were given prompts. Comparing behavioral outcomes, goals and planning, and regulation are frequently related to improvements in patients' clinical health status.

Use of Theory *(RQ4)* and its Effectiveness *(RQ5b)*

A mere 32 studies referred to a theory (32/101, 31.7%). However, for five studies (5/32, 15.6%), there was no indication of the exact theory except for the claim that the investigation was theory-driven. In total, 17 different behavior change theories underpinned the mHealth research that went into this review (Table 11).

Most prominent were the Transtheoretical Model, the Social Cognitive Theory (5/32, 15.6% each), and the Information-Motivation-Behavioral Skills Model (4/32, 12.5%). Four studies took a multi-theory approach (4/32, 12.5%). Most often, theory guided the design of mHealth (16/32, 50.0%). In seven studies, theory served the evaluation of usage (7/32, 21.9%), and in four studies the evaluation of health-related effects (4/32, 12.5%). In five studies, theory played a role in both the design and subsequent evaluation of health-related effects of mHealth (5/32, 15.6%). Yet, empirical testing of theoretical constructs played a marginal role at best.

Behavioral determinants of mHealth use were assessed in seven studies (7/101, 6.9%), four of which were explicitly theory-based (4/7, 57.1%). The pathway of behavioral determinants on health-related effects was modelled in six studies (6/101, 5.9%), of which, again, only half were explicitly theory-based (3/6, 50.0%).

Studies referring to theory did not achieve a higher percentage of overall effectiveness on health-related outcomes than studies not referring to theory (Table 12). Also, the rate of overall ineffectiveness did not differ substantially between studies with (4/26, 15.4%) or without a theory base (9/57, 15.8%). Studies drawing on multiple theories were effective; but again, their sparse occurrence does not allow for a definite conclusion. Of all theories that appeared in several studies, the Transtheoretical Model was the least effective across outcome types, followed by the Health Belief Model and the Self-Efficacy Theory. Hence, studies using the Information-Motivation and the Social-Cognitive Theory had a greater success rate.

Relation between mHealth use and health-related outcomes (*RQ6*)

Only a small friction of studies assessed associations between mHealth use and health-related outcomes (11/96, 11.5%). Overall, results are inconclusive. While few studies were able to link more frequent mHealth use to better self-management performance (3/4, 75.0%) and improved health status (4/9, 44.4%), others found improvements in behavioral (1/4, 25.0%), emotional (1/1, 100.0%), and clinical outcomes (5/9, 55.6%), regardless of the frequency of mHealth use.

Discussion

While previous evidence syntheses demonstrate the effectiveness of mHealth for chronic disease self-management, there is a lack of an advanced systematization of mHealth across the mobile media ecosystem, and a comprehensive overview of the status quo of mHealth research from usage to health-related effects. This systematic review of 101 studies in the context of diabetes type 1 and type 2, asthma, and COPD set out to address these deficits.

Clinical effects were the most examined and most often positively influenced outcome type (Alwashmi et al., 2016; Farzandipour et al., 2017; Kitsiou et al., 2017), followed by behavioral and cognitive outcomes. Emotional outcomes and quality of life were assessed far less and were also the outcome types with the smallest share of significant positive effects (Wang et al., 2017). The temporal flow of mHealth use involving patients' adoption decisions, post-adoptive satisfaction ratings, and continued use patterns played a marginal role in most studies—if at all (Hui et al., 2017). Except for self-reported satisfaction ratings, usage outcomes were primarily automatically recorded by the retention or engagement rate.

The present work focused on a detailed characterization of mHealth for chronic disease self-management, which provides insights into the self-management tasks, technological properties, and integrated strategies in mobile solutions. While the richness of the generated systematization demonstrates the versatility of mHealth, the occurrence of individual items makes it clear that some characteristics dominate research efforts. Starting with the primary use of mHealth for medical management, the emphasis on strengthening adherence extends through media attributes with mainly regulatory and informative BCTs. Despite the high degree of tailored systems, the individual needs of emotional management are not sufficiently addressed (Nolte & Osborne, 2013), also precisely because social support mostly remained at the unspecific or practical level than emotional. The urgency for improved mHealth solutions for emotional management is underscored by the consistently poor effects on emotional outcomes.

As far as the technological properties of mHealth are concerned, one cannot assert that researchers make full use of mobile media ecosystem when designing interventions. This contrasts previous research findings on the multifaceted mHealth repertoires patients hold in the real world (Rossmann et al., 2019). Nonetheless, an interesting pattern emerged regarding associated health-related outcomes: More basic systems, i.e., (two-way) push-media including cell phones, SMS, private chats, and notifications were more successful in improving cognitive, behavioral, and clinical outcomes, while more advanced systems, i.e., interactive pull-media including smartphones, apps, and self-tracking systems, performed worse at these levels. However, more advanced systems achieved improvements on the emotional level and quality of life more frequently. Of note, contrary to previous evidence (Farzandipour et al., 2017; Hui et al., 2017), this review found that the share of effective studies on the cognitive, behavioral, and clinical levels was higher for single-feature systems than for multi-feature systems. With regard to BCTs, almost all BCTs exhibited comparable overall effectiveness. Interestingly, however, rewards (including gamification) and affirmative statements about self-belief stood out as particularly ineffective techniques. This suggests that mHealth strategies based on extrinsic incentives and third-party persuasion may be less effective in supporting patients' self-management. This notion is confirmed by evidence in the context of the Self-Determination Theory applied to health behavior, that demonstrates that extrinsically motivated behavior is less stable than intrinsic motivation (Deci & Ryan, 2000; Knox et al., 2021).

Nevertheless, the fact that none of the commonly employed characteristics of mHealth achieved consistently high effectiveness, i.e., 100% overall effectiveness, must not be neglected. This suggests that there is no one-size-fits-all solution. Instead, individual predictors must determine the benefits of mHealth. However, with a few exceptions, the study of behavioral determinants of mHealth use and health-related effects was largely absent. Hence, it is once again confirmed that theory is underused and not sufficiently explicit in mHealth research (Chib & Lin, 2018). Based on this superficial use of theory and the small sample size, it is not surprising that there was no difference in health-related effects of studies mentioning or not mentioning a theory. This finding corresponds to the recent meta-analysis conducted by Qin et al. (2022) but contrasts with the prevailing state of research stressing the benefits of theory in digital (Middelweerd et al., 2014; Riley et al., 2011; Webb et al., 2010) and traditional health behavior interventions (Rossmann, 2015; Stehr et al., 2022; Glanz & Bishop, 2010). Finally, supporting the idea of individually varying effectiveness of mHealth, this review showed that health-related outcomes might depend on the intensity of mHealth use (Karnowski & Reifegerste, 2020; Sawalha & Karnowski, 2022; Stehr et al., 2020). But results remain inconclusive.

Scientific implications

Looking at our findings through the lens of the O_1-S-O_2-R model, we can discern implications and directions for future studies in this research field.

Starting from the centerpiece, the stimulus (S), this review found that it is worth breaking down mHealth into single tool characteristics, from which we generated a comprehensive systematization that future studies can draw on. In an effort to standardize future mHealth research and overcome quality deficiencies in reporting (see mERA checklist results), the systematization highlights the importance of using *unambiguous terminology* and *uniform reporting standards*. Furthermore, the health-related benefits of mHealth can only be reaped if there is sufficient understanding about how patients accept and use mHealth. Thus, upcoming research needs to capture mHealth use adequately by comparing effectiveness of mHealth use with non-mobile and non-digital interventions and overtime. Also, future studies need to integrate use in effects research to uncover associations and reciprocal effects in the long-term.

The most significant room for development in mHealth research lies at the inter-mediate stages, the pre- (O_1) and postexposure orientations (O_2). Very few studies mentioned a theory, even fewer studies went beyond the mere mention and tested the proposed theoretical constructs. Hence, the integration of theory in future mHealth research needs to be more precise in order to uncover predictive behavioral determinants of mHealth use and effects.

Speaking of health-related effects (R), effectiveness was often only measured at the clinical level. Certainly, laboratory parameters are considered the gold standard as they are not prone to sources of error (e.g., subjective misperceptions). Yet relevant insights about cognitive, behavioral, and emotional outcomes of mHealth use might be overlooked. Thus, future research must match the envisaged self-management tasks of mHealth with outcome measures to adequately capture the full spectrum of health-related effects of mHealth.

Limitations

Given the broad scope of this review, the comparability of included studies is limited. Due to the methodological heterogeneity and high variance of considered outcomes, we were obliged to apply a fairly superficial coding system for effectivity assessments, i.e., binary statements about (non-)significant positive effects were made, but not about their strength and clinical value. Moreover, small case numbers concerning specific elements (e.g., certain tool characteristics, theories) make it difficult to draw robust conclusions. Furthermore, this review is limited by the fact that data extraction was performed by one author, hence intercoder reliability is not assured. To counteract this limitation, the first author coded every study twice. Additionally, every uncertainty during coding was documented and consulted with the second author. Owing to continuous technological advancements the systematization of mHealth is by no means complete but is subject to constant advancements. Thus, upcoming reviews can progressively extend and refine our systematization. Furthermore, by restricting the inclusion criteria and updating the searches, a subsample of the included studies can be formed that is appropriate for meta-analysis, in order to gain more in-depth insights into the size and interrelations of effects.

Conclusions

This systematic review went beyond the mere question of “Does mHealth for chronic disease self-management work?” to a more nuanced examination of effectiveness. This investigation resulted in a comprehensive assessment, which offers valuable insights for future research and practitioners. Scholars can draw on an advanced systematization of mHealth characteristics as well as important findings for necessary next research steps, as outlined above. Furthermore, our results have practical implications: If the goal is to enhance patients’ disease knowledge and promote medical and conditional behaviors, mobile self-management solutions should be easy to integrate into patients’ lives and not require much effort to use (i.e., push-media). However, when seeking emotional comfort, patients should be offered systems that they can access when needed (i.e., pull-media). Although results are scattered, more functional BCTs (e.g., goals and planning, feedback and monitoring, social support, shaping knowledge, natural consequences) appear more successful than extrinsic rewards and affirmations. The results can inform the improvement and advancement of evidence-based disease self-management programs.

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Tables and Figures

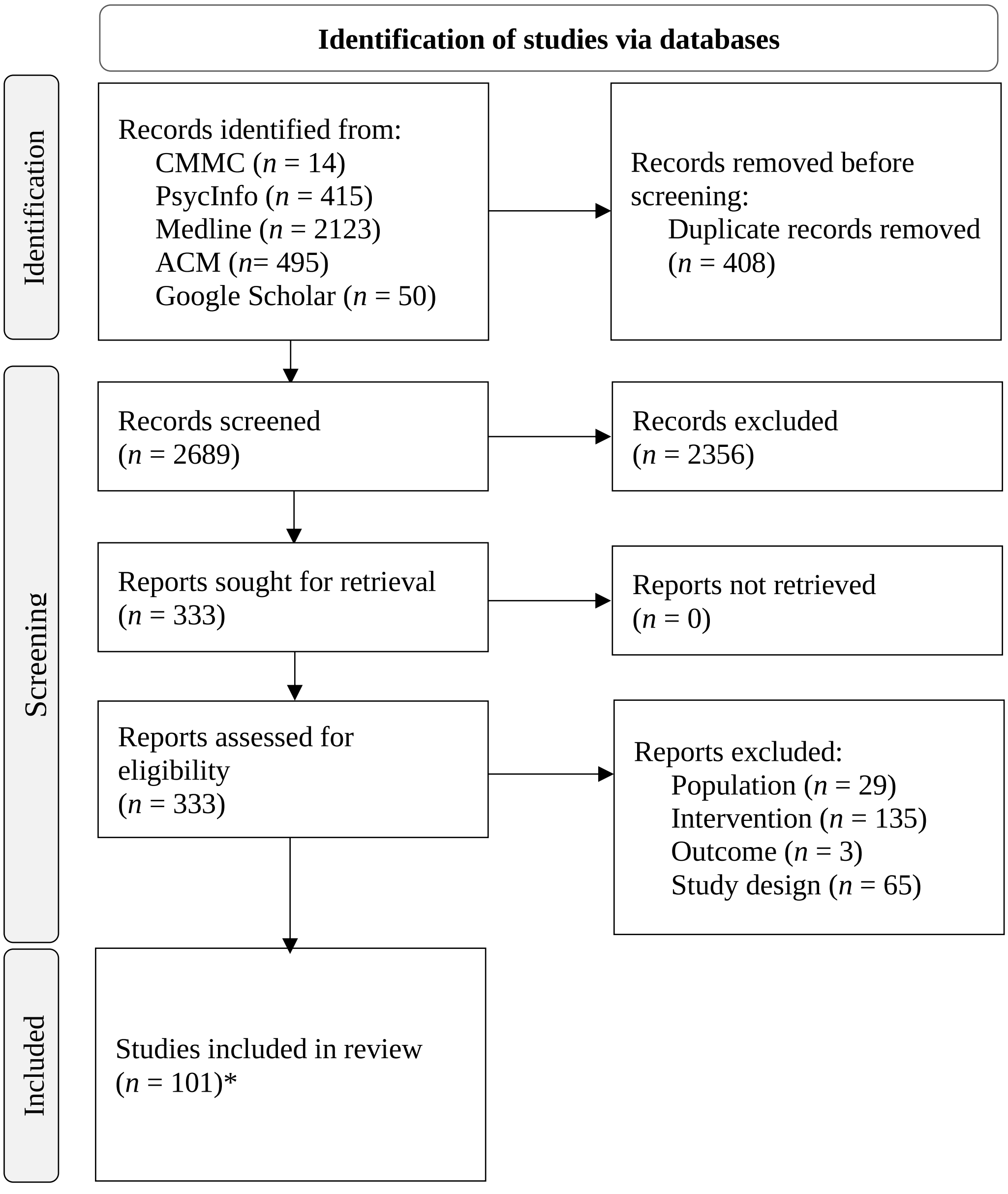
Figure 1. *Review framework following the O_1-S-O_2-R logic*

Preexposure orientations (O_1)	**Stimulus (S)**	**Postexposure orientations (O_2)**	**Response (R)**
Explanatory concepts Theories and determinants on mHealth use	*Explanatory concepts* Theories on the design of mHealth *Tool characteristics* Tasks Devices Channels Attributes BCTs *Outcomes* Adoption, post-adoption, continued use	*Explanatory concepts* Theories and determinants on mHealth effects	*Outcomes* Health-related effects of mHealth use

Table 1. *Inclusion and Exclusion Criteria*

Category	Inclusion criteria	Exclusion criteria
Population	Patients of all age groups with diagnosed type 1 diabetes, type 2 diabetes, asthma, or COPD as main users of mHealth	People with no or other chronic diseases (this includes reversible stages such as prediabetes); Healthcare professionals or informal caregivers as main users of mHealth
Intervention	Chronic disease self-management interventions using mobile media	Chronic disease self-management interventions without mobile media
Comparator	Not applicable. Observational studies may not have a comparator; Control or comparison groups may receive no, traditional, offline, or non-mobile digital interventions	
Outcome	Tool characteristics of mHealth (envisaged self-management tasks, device, platform, media attribute, and BCT) Theory base, behavioral determinants Adoption, post-adoption, and continued use of mHealth Health-related effects of mHealth use	Cost-effectiveness of mHealth
Study Design	Quantitative interventional and observational studies	Qualitative studies, content analyses design studies without empirical testing, evidence syntheses, theoretical treatises, research-in-progress, editorials, think-pieces

Figure 2. *PRISMA Flowchart of Systematic Review Search Process*



Note. *One paper reports two separate studies, and two papers report on the same study. Thus, both the number of included papers and included studies is 101.

Table 2. *mERA Results*

Items	Occurance rate	
	n	%
1. Infrastructure	0	0.0
2.Technology platform	69	71.9
3. Interoperability	30	31.3
4. Intervention delivery	77	80.2
5. Intervention content	62	64.6
6. Content testing	42	43.8
7. User feedback	50	52.1
8. Access of individual participants	59	61.5
9. Cost assessment	7	7.3
10. Adopting input	54	56.3
11. Limitation for delivery at scale	57	59.4
12. Contextual adaptability	25	26.0
13. Replicability	51	53.1
14. Data security	21	21.9
15. Compliance with guidelines	47	49.0
16. Fidelity of the intervention	68	70.8

Note. n = 96 (referring to interventional studies).

Table 3. *Outcomes of Interest*

Outcomes of interest	Occurrence rate	
	n	%
Only use		
Adoption	3	3.0
Post-adoption	4	4.0
Continued use	4	4.0
Adoption and continued use	1	1.0
Post-adoption and continued use	2	2.0
Only health-related effects		
Health-related effects	28	27.7
Use and health-related effects		
Adoption and effects	7	6.9
Post-adoption and effects	12	11.9
Continued use and effects	11	10.9
Adoption, continued use, and effects	1	1.0
Adoption, post-adoption, and effects	3	3.0
Post-adoption, continued use, and effects	15	14.9
Adoption, post-adoption, continued use, and effects	10	9.9

Note. n = 101.

Table 4. *Health-Related Outcome Measures*

Health-related outcomes	Occurrence rate	
	n	%
Cognitive	42	48.3
Knowledge	20	27.6
Self-efficacy	24	22.9
Perceived benefits	1	1.2
Perceived barriers	1	1.2
Perceived severity	1	1.2
Illness beliefs	4	4.6
Confidence in healthcare	2	2.3
Behavioral	62	71.3
Overall self-management behavior	36	41.4
Medication adherence	25	28.7
Diet/weight	6	6.9
Physical activity/exercise	8	9.2
Smoking cessation	3	3.5
Unplanned healthcare visits/hospitalizations	16	18.4
Emotional	18	20.7
Distress/depression	14	16.1
Perceived family/friend social support	7	8.1
Quality of life	25	28.7
Clinical	68	78.2
Laboratory/metabolic parameters	62	71.3
Self-reported health status	9	10.3

Note. n = 87.

Table 5. *Health-Related Effectivity Assessment: Envisaged Self-Management Tasks*

Self-management task	Number of studies with a significant effect on resp. outcomes out of total number of studies that examined this type of outcome										Overall effective studies[1] out of total	
	Cognitive		Behavioral		Emotional		Quality of life		Clinical			
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Knowledge	22/37	59.5	30/48	62.5	5/17	29.4	8/20	40.0	36/56	64.3	31/69	44.9
Medical	19/34	55.8	36/56	64.3	4/16	25.0	10/23	43.5	39/62	62.9	35/76	46.1
Condition	16/31	51.6	28/46	60.9	4/15	26.2	10/20	50.0	37/56	66.1	30/65	46.2
Emotional	9/19	47.4	18/26	69.2	3/14	21.4	6/12	50.0	20/31	64.5	15/36	41.7

Note. Because some studies included more than one self-management task and/or examined more than one outcome, the cases presented here are not independent samples.
[1] Displayed is the number of those studies finding an influence on the respective types of outcomes.

Table 61. *Health-Related Effectivity Assessment: Mobile Devices*

Device	Number of studies with a significant effect on resp. outcomes out of total number of studies that examined this type of outcome										Overall effective studies[1] out of total	
	Cognitive		Behavioral		Emotional		Quality of life		Clinical			
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Smart device	17/29	58.6	25/43	58.1	5/11	45.4	8/18	44.4	28/47	59.6	26/58	44.8
Cell phone	7/11	63.6	13/16	81.3	1/7	14.3	2/5	40.0	13/20	65.0	13/25	52.0
Transfer to main device												
Bluetooth	4/8	50.0	8/14	57.1	1/3	33.3	3/7	42.9	9/15	60.0	6/17	35.3
Plug	1/1	100	--	--	--	--	--	--	2/2	100	2/2	100
Manual	4/8	50.0	8/10	80.0	1/4	25.0	3/6	50.0	7/11	63.6	7/13	53.9

Note. Because some studies examined more than one outcome, the cases presented here are not independent samples.
[1] Displayed is the number of those studies finding an influence on the respective types of outcomes.

Table 72. *Health-Related Effectivity Assessment: Platforms*

Platforms	Number of studies with a significant effect on resp. outcomes out of total number of studies that examined this type of outcome										Overall effective studies[1] out of total	
	Cognitive		Behavioral		Emotional		Quality of life		Clinical			
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
App	13/23	56.5	21/35	61.3	5/10	50.0	7/16	43.8	23/38	60.5	24/48	45.8
SMS	8/12	66.7	12/16	80.0	1/7	14.3	2/5	40.0	14/21	66.7	13/26	50.0
Website	1/3	33.3	1/3	33.3	0/1	0.0	1/2	50.0	0/2	0.0	2/3	66.6
MMS	2/2	100	2/3	66.7	--	--	--	--	2/4	50.0	2/4	50.0
Social Media	--	--	1/1	100	--	--	--	--	1/1	100	1/1	100
Voice telephony	--	--	1/1	100	--	--	--	--	1/1	100	1/1	100
Multi-platform	2/7	28.6	3/8	37.5	0/4	0.0	3/6	50.0	8/13	61.5	4/15	26.7
Degree of Interactivity												
Interactive pull-media	15/27	55.6	24/42	57.1	5/11	45.5	8/18	44.4	25/40	56.8	23/55	41.8
One-way push-media	6/9	66.7	9/11	81.8	1/3	33.3	1/4	25.0	7/12	58.3	9/16	56.3
Two-way push-media	3/4	75.0	5/6	83.3	0/4	0.0	1/1	100	9/11	81.8	7/12	58.3

Note. Because some studies included more than one platform and/or examined more than one outcome, the cases presented here are not independent samples.
[1] Displayed is the number of those studies finding an influence on the respective types of outcomes.

Table 8. *Health-Related Effectivity Assessment: Media Attributes*

Media attribute	Number of studies with a significant effect on resp. outcomes out of total number of studies that examined this type of outcome										Overall effective studies[1] out of total	
	Cognitive		Behavioral		Emotional		Quality of life		Clinical			
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
Communication	17/26	65.4	25/37	67.6	4/14	28.6	6/15	40.0	26/43	60.5	24/53	45.3
Co-user	15/24	62.5	23/35	65.7	4/14	28.6	6/15	40.0	25/40	62.5	22/49	44.9
Chatbot	1/1	100	1/1	100	0/1	0.0	1/3	33.3	3/3	100	1/3	33.3
Embodied virtual assistant	--	--	--	--	--	--	--	--	--	--	--	--
Private chat	9/13	69.2	13/16	81.3	1/7	14.3	2/8	25.0	16/23	69.6	12/26	46.2
Voice/Video calls	4/6	66.7	7/9	77.8	2/3	66.7	2/4	50.0	5/10	50.0	5/11	45.5
Public forum	2/5	40.0	6/8	75.0	2/4	50.0	2/3	66.7	5/9	55.6	5/10	50.0
Self-tracking	13/26	50.0	20/37	54.1	5/13	38.5	8/19	42.1	25/42	59.5	21/52	40.4
Smart visit report	2/4	50.0	4/8	50.0	2/4	50.0	8/19	42.1	6/10	60.0	5/13	38.5
Camera	1/2	50.0	1/2	50.0	--	--	--	--	0/1	0.0	1/2	50.0
Database	1/3	33.3	1/3	33.3	0/1	0.0	1/3	33.3	4/5	80.0	2/7	28.6
Map	1/1	100	0/1	0.0	--	--	1/2	50.0	2/2	100	1/3	33.3
Notification	10/21	47.6	18/28	64.3	4/12	33.3	7/13	53.9	23/35	65.7	22/44	50.0
Resources	12/20	60.0	19/29	65.5	3/11	27.3	5/10	50.0	15/28	53.6	16/38	42.1
Written	9/17	52.9	14/21	66.7	3/11	27.3	5/9	55.6	11/21	52.4	12/29	41.4
Video	5/6	83.3	8/14	57.1	2/4	50.0	4/5	80.0	6/10	60.0	7/17	41.2
Image	1/1	100	3/4	75.0	--	--	1/1	100	3/4	75.0	4/5	80.0
Gif	--	--	0/1	0.0	--	--	--	--	0/1	0.0	0/1	0.0
Audio	1/1	100	1/1	100	--	--	--	--	1/1	100	1/1	100
(Serious) game	1/1	100	2/2	100	--	--	--	--	1/2	50.0	1/2	50.0
Number of features												
Single-feature	9/12	75.0	15/19	79.0	1/2	50.0	2/6	33.3	14/21	66.7	15/25	60.0
Multi-feature	15/28	53.6	23/40	57.5	5/16	31.3	8/17	47.1	27/46	58.7	24/58	41.4

Note. Because some studies included more than one media attribute and/or examined more than one outcome, the cases presented here are not independent samples.

[1] Displayed is the number of those studies finding an influence on the respective types of outcomes.

Table 9. *Inductively Derived BCTs*

BCT	Definition	Examples
2. Feedback and monitoring		
2.8 Alerts signaling critical condition	Monitor and provide feedback on the outcome(s) of behavior in the form of warning alerts for critical health conditions *Note: If the alert contains a detailed plan of emergency behavior, also code 1.4, action panning*	"Algorithm that detects and informs the user of consecutive out-of-range readings for the same context (eg, 3 consecutive high dinner readings) and prompts the user to identify the likely cause of the trend and potential fixes." (*Goyal et al., 2017, p. 4)[6]
4. Shaping knowledge		
4.5 Test of knowledge	To encourage or reinforce the learning effect, provide test questions that relate to the program material *Note: If a test involves reward or punishment, also code one or more of: 10. Reward and threat*	"Intervention participants received both declarative messages related to their preselected SCB and quiz-type questions about general T1D knowledge with automated replies indicating the correct answer." (*Kaushal et al., 2022, p. 122)
6. Comparison of behavior		
6.4 Performance ranking	Draw attention to others' performance to allow comparison with the person's own performance in the form of a ranking system *Note: also code 6.2, Social comparison and 10.2 Gamification*	"*bant* also includes a leaderboard for users to see where they rank compared with their peers" (*Goyal et al., 2017, p. 4)
10. Reward and threat		
10.12 Gamification	Create the feeling of progress by encouraging and rewarding behavior or outcome(s) of the behavior with virtual points or a level-up *Note: If points/levels are compared with others' performance, also code 6.2, Social Comparison and 6.4 Performance ranking; if collecting points is rewarded, also code one or more of: 10. Reward and threat*	"Points are assigned for each task completed and accumulate over time. The total number of points through the course of use of the app served as a reminder to the participant regarding how far they progressed." (*Batch et al., 2021, p. 3).

[6] Primary studies included in the study corpus of this review are marked with an asterisk (*).

BCT	Definition	Examples
16. Covert learning		
16.4 Inspirational simulation	Prompt simulation of decision-making in an alternate context to inspire transfer of experience to the person's disease-specific decision-making	"This 12-min game was played once, and it consisted of an engaging scenario of an easy-to-relate-to person with multiple real-world pressures (job and family) with "good excuses" for their obvious non-adherent health care behavior. Next, the subject immerses herself into this story and deals with these real-world pressures to reflect their typical behavior in their real life." (*Joshi et al., 2018, p. 272)
17. Tailoring		
	Customize content to the demographic characteristics, preferences, and needs of the individual user *Note: Tailoring is always combined with another technique*	"Each person received 75% of their messages tailored to the top three barriers to adherence that they reported in their Barriers to Diabetes Adherence assessment." (*Mulvaney et al., 2012, p. 2)

Table 10. *Health-Related Effectivity Assessment: BCTs*

BCT	Number of studies with a significant effect on resp. outcomes out of total number of studies that examined this type of outcome										Overall effective studies[1] out of total	
	Cognitive		Behavioral		Emotional		Quality of life		Clinical			
	n	%	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Goals and planning	15/27	55.6	30/44	68.2	4/14	28.6	8/20	40.0	35/53	66.0	30/63	47.6
Feedback and monitoring	13/26	50.0	20/37	54.1	5/13	33.3	8/19	42.1	25/42	59.5	21/52	40.4
Social support	15/24	62.5	23/35	65.7	4/14	28.6	6/15	40.0	25/40	62.5	22/49	44.9
Shaping knowledge	21/37	56.8	32/49	65.3	5/17	29.4	9/21	42.9	35/56	62.5	32/70	45.7
Natural consequences	13/19	68.4	16/24	66.7	4/8	50.0	4/8	50.0	15/27	55.6	15/34	44.1
Comp. of behavior	3/5	60.0	7/9	77.8	1/2	50.0	2/5	40.0	5/10	50.0	5/10	50.0
Associations	16/29	55.2	27/43	62.8	4/16	25.0	9/19	47.4	30/49	61.2	26/60	43.3
Comp. of outcomes	8/14	57.2	13/19	68.4	2/9	22.2	2/8	25.0	15/22	68.2	11/25	44.0
Reward and threat	3/9	33.3	6/11	54.6	1/5	20.0	2/6	33.3	1/11	9.1	1/12	8.3
Regulation	19/34	55.9	36/56	64.3	4/16	25.0	10/23	43.15	39/62	62.9	35/76	46.1
Antecedents	1/3	33.3	4/5	80.0	0/1	0.0	3/5	60.0	2/6	33.3	2/6	33.3
Scheduled consequences	--	--	1/1	100	0/1	0.0	0/1	0.0	1/1	100	1/1	100
Self-belief	1/7	14.3	5/9	55.6	0/3	0.0	1/5	20.0	7/13	53.9	3/13	23.1
Covert learning	--	--	1/1	100	--	--	--	--	1/1	100	1/1	100
Tailoring	16/30	53.3	25/44	56.8	4/13	30.8	8/21	38.1	30/51	58.8	25/61	41.0

Note. Because some studies included more than one BCT and/or examined more than one outcome, the cases presented here are not independent samples.

[1] Displayed is the number of those studies finding an influence on the respective types of outcomes.

Figure 3. *mHealth Toolbox for Chronic Disease Self-Management*

TASKS

GENERIC TASKS
Medical (91.6%)
Knowledge (81.8%)
Condition (76.5%)
Emotional (42.3%)

DIABETES-SPECIFIC
Blood glucose testing, insulin administration, oral medication (93.5%); diet and healthy weight (87.0%); physical activity and exercise (84.4%); smoking cessation (28.6%), foot care (36.7%), healthy coping (41.6%)

RESPIRATORY-SPECIFIC
Peak flow measurement, inhaler use, and oral medication (85.7%), action planning (76.2%), physical activity and pulmonary rehabilitation (61.9%), and smoking cessation (47.6%)

DEVICES

MAIN DEVICE
Smartphone (57.1%)
Cell phone (20.4%)
Tablet (3.1%)
at least smart device (9.2%); no more than a cell phone (10.2%)

ADDITIONAL EQUIPMENT
Medical instruments: Glucometer (65.9%), glucose sensor (9.1%), pulse oximeter (11.4%), peak flow meter (9.1%), inhaler adapter (4.6%), spirometer (2.3%), forehead thermometer (2.3%)
Other: Activity tracker (4.6%); indoor air quality monitor (4.6%)

TRANSFER TO MAIN DEVICE
Bluetooth-connected (50.0%), plug (4.6%), manual (45.4%)

PLATFORMS

PLATFORM
App (58.2%)
SMS (29.6%)
Website (5.1%)
MMS (5.1%)
Social media (1.0%)
Voice telephony (1.0%)
Multi-platform (18.4%)

DEGREE OF INTERACTIVITY
Interactive pull-media (67.4%)
One-way push-media (17.4%)
Two-way push-media (15.3%)

SCHEDULED CONTACT
Flexible schedule (61.2%)
Fixed schedule (34.7%)

ATTRIBUTES

COMMUNICATION
Integration of: co-users (59.1%), chatbots (5.1%), embodied virtual assistant (1.0%)
Portals: private chats (29.6%), voice and video calls (28.6%), public forums (12.2%)

SELF-TRACKING
Self-tracking (65.3%)
Supported by: smart visit report (18.4%) camera documentation (3.1%), databases (8.2%), maps (3.1%)

NOTIFICATIONS
Unilateral notifications (51.0%)

RESOURCES
Written (33.7%), videos (19.4%), images (7.1%), gifs (1.0%), audio (2.0%), (serious) games (2.0%)

BCTS

HIGHER-ORDER BCTs
Regulation (91.8%)
Shaping knowledge (81.6%)
Tailoring (76.5%)
Goals and planning (73.5%)
Associations (69.4%)
Feedback and monitoring (65.3%)
Social support (62.2%)
Natural consequences (34.7%)
Comparison of outcomes (29.6%)
Self-belief (16.3%)
Reward and threat (15.3%)
Demonstration of behavior (11.2%)
Antecedents (6.1%)
Scheduled consequences (1.0%)
Covert learning (1.0%)

Table 11. *Theory Base*

Theory base	Theory for design		Theory for use		Theory for health-related effects		Theory for design and health-related effects		Total	
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
Unspecified	4	25.0	--	--	1	25.0	--	--	5	15.6
CT	1	6.3	--	--	--	--	--	--	1	3.1
BCW	1	6.3	--	--	--	--	--	--	1	3.1
BCT	1	6.3	--	--	--	--	--	--	1	3.1
BIT	--	--	--	--	--	--	1	20.0	1	3.1
IBM	1	6.3	1	14.3	--	--	2	40.0	4	12.5
COM-B	1	6.3	--	--	--	--	--	--	1	3.1
CSM	1	6.3	--	--	--	--	--	--	1	3.1
NASSS	--	--	1	14.3	--	--	--	--	1	3.1
HPM	--	--	--	--	--	--	1	20.0	1	3.1
SGT	1	6.3	--	--	--	--	--	--	1	3.1
SST		--	--	--	--	--	1	20.0	1	3.1
HBM	1	6.3	--	--	1	25.0	--	--	2	6.3
SET	--	--	--	--	1	25.0	1	20.0	2	6.3
SCT	2	12.5	--	--	1	25.0	2	40.0	5	15.6
TTM	3	18.8	1	14.3	--	--	1	20.0	5	15.6
TAM	--	--	2	28.6	--	--	--	--	2	6.3
UTAUT	--	--	2	28.6	--	--	--	--	2	6.3
Number or theories										
Single-theory	15	93.8	7	100.0	4	100.0	2	40.0	28	87.5
Multi-theory	1	6.3	--	--	--	--	3	60.0	4	12.5

Note. n = 32. Because some studies included more than one theory base, the cases presented here are not independent samples. CT = Complexity theory, BCW = Behavior Change Wheel; BCT = Behavior Change Theory; BIT = Behavior Intervention Theory; IBM = Information-Motivation-Behavioral Skills Model; COM-B = Capability-Opportunity-Motivation-Behavior Model; CSM = Common-Sense Model of Self-Regulation; NASSS = Nonadoption, Abandonment, Scale-up, Spread, and Sustainability framework; HPM = Health Protection Model; SGT = Social Graph Theory; SST = Social Support Theory; HBM = Health Belief Model; SET = Self-Efficacy Theory; SCT = Social Cognitive Theory; TTM = Transtheoretical Model; TAM = Technology Acceptance Model; Unified Theory of Acceptance and Use of Technology.

Table 12. *Health-Related Effectivity Assessment: Theory Base*

Theory base	Number of studies with a significant effect on resp. outcomes out of total number of studies that examined this type of outcome										Overall effective studies[1] out of total	
	Cognitive		Behavioral		Emotional		Quality of life		Clinical			
	n	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
Use of theory	10/17	58.8	10/20	50.0	4/6	66.7	4/10	40.0	10/18	55.6	11/26	42.3
No theory	14/23	60.9	28/39	71.8	2/12	16.7	6/13	46.2	31/49	63.3	28/57	49.2
Number of theories												
Single-theory	8/14	57.1	8/17	47.1	4/5	80.0	4/9	44.4	9/15	60.0	9/22	40.9
Multi-theory	2/3	66.7	2/3	66.7	0/1	0.0	0/1	0.0	1/3	33.3	2/4	50.0
Theory												
Unspecified	1/3	33.3	0/3	0.0	1/2	50.0	2/3	66.7	1/3	33.3	2/4	50.0
CT	--	--	1/1	100	--	--	--	--	1/1	100	1/1	100
BCW	1/1	100	1/1	100	--	--	0/1	0.0	0/1	0.0	1/1	100
BCT	--	--	1/1	100	--	--	--	--	1/1	100	1/1	100
BIT	1/1	100	--	--	--	--	--	--	--	--	1/1	100
IBM	1/2	50.0	1/3	33.3	1/1	100	1/1	100	1/1	100	2/3	66.7
COM-B	0/1	0.0	0/1	0.0	--	--	0/1	0.0	0/1	0.0	0/1	0.0
CSM	--	--	--	--	--	--	--	--	1/1	100	1/1	100
HPM	1/1	100	--	--	1/1	100	--	--	--	--	1/1	100
SGT	--	--	--	--	--	--	--	--	--	--	--	--
SST	1/1	100	0/1	0.0	--	--	--	--	0/1	100	1/1	100
HBM	1/1	100	0/1	0.0	--	--	--	--	1/1	100	1/2	50.0
SET	1/2	50.0	1/1	100	0/1	0.0	0/1	0.0	2/3	66.7	1/2	50.0
SCT	3/4	75.0	4/5	80.0	0/1	0.0	0/1	0.0	2/3	66.7	3/5	60.0
TTM	1/2	50.0	0/3	0.0	--	--	0/1	0.0	0/3	0.0	1/3	33.3

Note. Because some studies included more than one theory base and/or examined more than one outcome, the cases presented here are not independent samples.
[1] Displayed is the number of those studies finding an influence on the respective types of outcomes.