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Chib, Arul; Lin, Sapphire H.

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Theoretical Advancements in mHealth:
A Systematic Review of Mobile Apps

Arul Chib
Nanyang Technological University

Sapphire H. Lin
Nanyang Technological University

Corresponding author. Arul Chib is an Associate Professor at the Wee Kim Wee School of Communication and Information, Nanyang Technological University

Email: arulchib@ntu.edu.sg Phone: (65) 6514 8390 Fax: (65) 6792 4329
31 Nanyang Link, WKWSCI Bldg Singapore 637718

Sapphire Lin was a doctoral student at Wee Kim Wee School of Communication and Information, Nanyang Technological University, at the time of writing.

Abstract

There are now few hundred thousand healthcare apps, yet there is a gap in our understanding of the theoretical mechanisms for which, and how, technological features translate into improved healthcare outcomes. In particular the technological convergence, within mobile health (mHealth) apps, of the processes of mass and interpersonal communication, and human-computer interaction requires greater parsing in the literature. This paper analyzed 85 empirical studies on mHealth apps using the Input-Mechanism-Output model. We found in the literature that, firstly, there is a greater emphasis on technological inputs (87%) of accessibility, usability, usage, and data quality, than health outputs (52%) such as system process efficiencies and individual level behavioral or health outcomes. Secondly, there is little evidence of explanatory mechanisms (19%) of how the effects of mHealth apps are achieved. While we believe that successful apps would require research that incorporates technological inputs, theoretical mechanisms and health outputs, such studies are a rarity ($n=3$). There is a minor increase in rigor with randomized control trials ($n = 5$), and a preponderance of discussion around social influence ($n = 8$) and gamification ($n = 7$), albeit in a scattered manner. We discuss the implications of the trend towards socialization and gamification findings in terms of future research, particularly in terms of study design guided by theoretical mechanisms.

Keywords: Apps, mHealth, review, serious games, social.

Theoretical Advancements in mHealth: A Systematic Review of Mobile Apps

Techno-deterministic perspectives have dominated the field of mobile health (mHealth), assuming that technological development and introduction are sufficient for achieving health outcomes. Early definitions of mHealth focused on a range of technical systems enabled by technical devices configured via cellular, wireless and Bluetooth networks (Yu, Wu, Yu, & Xiao, 2006). mHealth has since been characterized by a focus on mobile telecommunications in a variety of healthcare delivery services (Michael et al., 2010; Nacinovich, 2011), with the emergence of voice and text messaging (Fjeldsoe, Marshall, & Miller, 2009; Krishna, Boren, & Balas, 2009).

More recently, mHealth apps have become ubiquitous as a consequence of smartphone use. There are already 325,000 health apps in the market (Pohl, 2017), but empirical evidence on mHealth apps has made less headway than desired (Boudreaux et al., 2014). A more pertinent question might however address their effectiveness. The purpose of this review is to assess forthcoming trends of mHealth app research, and cast some light onto how these trends may develop in time to come, and their impact on health. Situated in scholarship, we offer a theoretically-driven review of the mHealth apps literature, asking two key research questions. First, in which sub-discipline of communications do we situate the study of mHealth apps? Second, can we explain the theoretical mechanisms behind the translation of technological factors into health outcomes? To do so, we reviewed the literature ($n = 85$) from 2012–2017 using the input-mechanism-output model.

Communication in Mobile Health

Studies in the health communication field examining technological interventions had previously focused primarily on the internet (Cassell, Jackson, & Cheuvront, 1998; Rice & Katz, 2000), culminating in eHealth (Kreps & Neuhauser, 2010). The internet initially acted as a source of mass communication, with individuals searching for health information online,

followed by convergence with interpersonal communication of two types. Kreps (2017) posits that the type 1 convergence involves individuals using health information online to initiate conversations with health professionals, such as their personal physician. Type 2 convergence, on the other hand, involves peer-to-peer communication online, such as that found in online social support groups (Chung, 2014). In contrast, the emergence of mHealth in the journal with a spate of introductory empirical studies was characterized by a period when studies veered towards either the mass and interpersonal communication spheres.

In the first group, reviews found text messages as a form of one-to-many (mass) communication for dissemination of health information (Cole-Lewis & Kershaw, 2010; Higgs et al., 2014). Examining empirical data from a variety of pilot studies, this group can be further sub-divided into two type of recipients, the first enhancing communication within the healthcare system, for example, to healthcare workers (Author, 2012; Lemay, Sullivan, Jumbe, & Perry, 2012). The second type of text messages provided information to end-beneficiaries or patients (Evans, Abrams, Poropatich, Nielsen, & Wallace, 2012; Parker, Dmitrieva, Frolov, & Gazmararian, 2012; Ybarra, Prescott, & Holtrop, 2014).

In the second group of mHealth studies, phone calls acted as a form of mediated one-to-one (interpersonal) voice communication between healthcare givers and patients (Katz, Mesfin, & Barr, 2012), or for peer support (Wollersheim, Koh, Walker, & Liamputtong, 2013). A review of mHealth in developing countries (Gurman, Rubin, & Roess, 2012) found evidence of two-way communication, though much of this comprised self-reported responses indicating compliance with a behavior recommended via text message. Other reviews demonstrated that two-way messaging was more effective than one-way texting in managing type 2 diabetes (Holcomb, 2015), and for improving medication adherence (Wald, Butt, & Bestwick, 2015). More recently, we have seen the advance of intervention designs using mobile phones text messaging that also involve peer support (Dailey et al., 2018) and

professional counseling (Martinez-Brockman, Harari, & Pérez-Escamilla, 2018). Perhaps these are instances of a variation of Type 1 convergence (Kreps, 2017), in which mHealth messages are disseminated via mass communication with the intent to foster interpersonal communication.

Positioning Mobile Apps in the mHealth Sphere

The emergence of mHealth apps, however, defies the neat categorizations of mass and interpersonal communications disciplines, or the communication convergence types posited as specific to health (Kreps, 2017). First, for clarity and for bounding the scope of this study, the term “mHealth apps” in this paper will refer to applications with functions related to human health, built to run on mobile smartphones. These functions can range from providing users with health-related information or instructions, tracking and sharing users’ health statistics with distinct stakeholders, interaction with computer-based agents such as games, or providing an interactive platform for communication with peers or health experts. We note that mHealth apps are unlike other types of traditional media, as these not only enable the convergence of former boundaries of mass and interpersonal communication processes, but are a platform for different forms of health promotion and communication across social networks. For example, Liu and Willoughby (2018) describe a study where a fitness app is combined with system-generated text messages, providing a conundrum whether this is mass or interpersonal communication. The individual interacts with the computing power on the mobile phone in the fitness app, and the computer system generates and disseminates a text message without need for human decision-making.

Evidently, mHealth, beyond being a medium for dissemination of messages and a conduit for conversations, introduces processes more akin to human-computer interaction (HCI). The ability for applications and servers to harness and store user data, allied with improved computation capabilities, both at the cloud and individual levels, are producing a

wealth of Big Data (Schneeweiss, 2014). These analyses have the potential to inform both the healthcare system and the individual user about lifestyle and treatment choices without the intervention of human healthcare providers. The potential elimination of healthcare providers, such as personal physicians, from the information and communication cycle, has serious implications, particularly given the growing complexity of mHealth apps. The See Me Smoke-Free technological development describes an app that includes access to online content, interactive features, reception of notifications and messages, tracking of personal habits, and the ability to call a helpline (Armin, Johnson, Hingle, Giacobbi, & Gordon, 2017). Given the plethora of technical features that apps afford, it is likely going to be increasingly difficult to parse out the differential effects of each one. Understanding the evolving role in mHealth apps of mass and interpersonal communication processes with a trend towards computer-based decision-making and interaction requires immediate investigation. Thus, this research study inquires: In which sub-discipline of communications do we situate the study of mHealth apps, and whether this is even possible? To do so, we need to identify the trends in mHealth app research.

Current Trends in Research on mHealth Apps

It is worth noting that we are yet to develop a body of scientific evidence of effectiveness (Bhansali & Armstrong, 2012), despite there being at least 259,000 mHealth apps in the app market (Skardziute, 2016), a 57 percent increase since 2015, an exponential increase that shows little sign of abating. More recently, the number has steadily grown to 325,000 (Pohl, 2017). An examination of mHealth app studies published five years hence indicates that there continues to be a focus on proof-of-concept, with studies describing pilot programs or technological development (Armin et al., 2017; Cameron et al., 2017), or adoption studies (Lin & Bautista, 2017). Both types of studies are sans evidence of effectiveness—hardly an improvement to the critiques raised by Sherry and Ratzan (2012).

We echo the notion that more research is needed to establish evidence for efficacy of mHealth apps (Boudreaux et al., 2014).

While the need for more empirical research on mHealth apps is evident, it is equally important to pause and take stock of the current literature on mHealth apps, to evaluate the status of current research, identify the gaps, provide directions for future research, and inform practice. There have been more reviews that analyze the content of mHealth apps on a surface level—for example, those purported to advise consumer uptake (Mendiola, Kalnicki, & Lindenauer, 2015)—than there are reviews dealing with literature that actually assesses the effectiveness of mHealth apps (Ghorai, Akter, Khatun, & Ray, 2014). Beyond advising consumers on which app is more trustworthy or more effective, it is time to assess the state of the research on mHealth apps, advise future research on mHealth apps, and recommend more effective development and use. We therefore propose our second research question: Can we explain the theoretical mechanisms behind the translation of technological factors into health outcomes?

To do so, we utilize the mHealth pathway model (Author, 2015), in which selected studies are categorized into inputs, mechanisms, and outputs. Input factors are what make a system work, mechanisms are how a system works, and output factors are what results from a system. The original model applies to mHealth apps by considering inputs as accessibility and usage factors that relate to technology development, mechanisms as individual- and psychosocial-level theoretical explanations for adoption and adherence, while outputs range from healthcare system outputs to individual health outcomes (see Figure 1).

-----FIGURE 1 HERE-----

Method

We note that this review aims to cover the spectrum of empirical research by conducting a thorough review of studies on mHealth apps using a broad lens without

focusing on any specific area of fitness or disease, nor any particular target audience or global region. The intent is not to provide an exhaustive summary of all studies in the area, but to provide a systematic status update of the field.

Search Methods and Criteria

The search for articles was conducted on the following databases: Web of Science, Scopus, PubMed, and PsycINFO. One reviewer searched the databases with the keywords: “mHealth” OR “mobile health” OR “m-health” OR “mobile-health” OR “health app” OR “health apps” AND “app” OR “apps”. Articles selected had to be peer-reviewed empirical studies published in English language. Further inclusion criteria streamlined focus to studies that actually tested an app on users or potential users. Thus, papers that focused only on technical development, opinion pieces, study protocol proposals and reviews were excluded, as were non-peer-reviewed articles.

The search results across all four databases were combined, leading to a collection of 684 articles. Duplicate citations were removed, bringing the total down to 400. One reviewer went through all titles, keywords, and abstracts to streamline the collection, screening them based on the inclusion/exclusion criteria. Full-length articles were downloaded, or requested from authors when they could not be found. 105 articles remained, with 290 removed after screening of titles and abstracts, and five papers irretrievable despite efforts to contact authors. Both reviewers agreed to remove 20 papers during the full-length review due to lack of fit with inclusion criteria. The final dataset for analysis comprised 85 articles from 2011 to 2016. Figure 2 illustrates the selection process.

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Some articles contained a mixture of empirical studies on mHealth apps and other content that met exclusion criteria, like design and development descriptions, or reviews of apps. In such cases, the paper was retained in the selection set, but only the relevant portions

of the paper were included for analysis.

Data Extraction and Analysis

The review was conducted based on the Cochrane Collaboration systematic review methodology (Higgins & Green, 2011) and qualitative review methodology (Ring, Ritchie, Mandava, & Jepson, 2010; Sandelowski & Barroso, 2002; Thomas & Harden, 2008). This included defining the review question and developing criteria for inclusion and exclusion of studies, a high sensitivity search for studies, selection and data extraction using a standardized form, and considering meta-analysis when appropriate, else presenting a narrative assessment.

For every paper in the dataset, information was extracted using a standardized form including fields for app descriptors; study descriptors; and factors relating to system input and output. Both reviewers analyzed the dataset to arrive at the themes answering the research questions posed. Statistical pooling of results was not possible due to extensive heterogeneity of study methods and results.

Findings

The final selected dataset covered studies on a relatively broad spectrum of apps such as: self-management, information and education, health data collection, diagnostic evaluation and measurement, intervention between healthcare worker and patient. Health areas covered in apps studied included: general wellness, physical activity, weight management, diet, mental and emotional health, cognition, cardiology, addiction (e.g., smoking and drugs), sexuality, disease management and evaluation (e.g., cancer, diabetes, and asthma), patient monitoring and tracking. Target audiences included: general public, healthcare workers, patients, and users of various age groups.

Trends in mHealth App Research

With respect to our first research question, the analysis proved inconclusive, with studies reporting apps that used a combination of mass and interpersonal communication, and HCI processes. More confounding than this convergence of processes was the lack of specification in terms of focus of research design, a theme we shall discuss in the following section on theoretical mechanisms. Nonetheless, three main trends allow for insights: randomized control trials, serious games and social influence.

Randomized Control Trial (RCT). There is a rise in RCT designs in the field ($n = 5$) (Direito, Jiang, Whittaker, & Maddison, 2015; Holmen et al., 2014; Rabbi, Pfammatter, Zhang, Spring, & Choudhury, 2015; Torbjørnsen et al., 2014; van Drongelen et al., 2014), suggesting a growing rigor in testing of app effects. However, a number of RCTs failed to show a significant intervention effect, although secondary outcomes were exhibited. Direito et al. (2015), evaluating 51 participant's physical activity, found neither differences in time to complete fitness tests, nor self-reported physical activity levels. Examining diabetes apps, Holmen et al. (2014) and Torbjørnsen et al. (2014) found no group differences in hemoglobin A_{1c} levels. There is preliminary evidence to suggest some success, as van Drongelen et al. (2014) demonstrated effects of the MORE energy mobile app to improve health-related behavior amongst 501 airline pilots.

Serious games. Seven studies investigated the gamification aspects of mHealth apps. On a positive note, gamification through the use of rewards and incentives, or a literal game component, increased willingness to use and adhere to an app (Boushey et al., 2015; Cafazzo, Casselman, Hamming, Katzman, & Palmert, 2012). Some serious games had communities or social influences that promoted health behavior (Lane, Armin, & Gordon, 2015; Ploderer, Smith, Pearce, & Borland, 2014; Silveira, van de Langenberg, et al., 2013). However, when an immersive app was compared with apps that were less immersive, no significant results were found (Direito et al., 2015).

Social influence. Overall, we find that the majority of studies view mHealth apps as a combination of mass communication dissemination and algorithms for HCI. In general, apps were designed to communicate generic formulaic recommendations, albeit tailored to individual inputs of certain variables. While these were broad trends, a growing preponderance of social influence was found in eight studies. Comparing individual app users with social ones, the latter felt more motivated to engage in health behaviors through emotional support from peers (Silveira, van het Reve, Daniel, Casati, & de Bruin, 2013). A number of studies indicated social support from peers (Monney, Penzenstadler, Dupraz, Etter, & Khazaal, 2015; Ploderer et al., 2014), peer feedback (Helander, Kaipainen, Korhonen, & Wansink, 2014), social presence of health practitioners with patients (Barnett, Harricharan, Fletcher, Gilchrist, & Coughlan, 2015), use of social networks and media (Cafazzo et al., 2012; Direito et al., 2015), and social contexts (Yang et al., 2015).

Although these studies explored apps that had social features, there is a need for greater clarity on whether and how these features contributed to the effectiveness of the app. The use of the terms “interpersonal” / “social” ran across a gamut of concepts; indeed, was often used quite loosely, usually related to the technical features of the mobile application. The lack of focus on theoretical mechanisms rendered this investigation too scattered for conceptual integration.

Inputs, Mechanisms, and Outputs of mHealth App Research

In relation to our second question, analysis of the dataset revealed that present scientific emphasis is on technology development rather than on health impacts, with explanatory frameworks de-emphasized (see Figure 3). These analytical figures are overlapping and not cumulative, because some papers contained more than one factor. Table 1 contains a summary of all the papers reviewed.

-----FIGURE 3 HERE-----

-----TABLE 1 HERE-----

Input Factors

Input factors were studied most frequently (87%, $n = 74$), largely oriented towards technological factors. The analytical results from these studies were categorized into four main themes: usability, usage, data quality, and accessibility. We note that these input factors, while useful for technology development, offer little guidance as to the information and communication processes occurring that might impact health outcomes.

Usability was the most regularly noted theme, appearing in 50 papers. Relevant studies explored how easily a mHealth app could be learnt and used, and how the design could be improved to better appeal to users. Such research was usually conducted with apps that were relatively new or undergoing pilot testing. Usage came next, appearing in 41 papers. Research was conducted on whether an app was downloaded or used, the frequency of use, the duration of use, the reach of the app, and user demographics. As usage statistics were mostly app-specific, these will not be covered in this review. Data quality was the third noted theme, studied in 25 papers. This refers to the accuracy and privacy of data, particularly health records, and the usefulness of content in informational mHealth apps. Accessibility was the last common input theme, studied in 15 papers. It refers to the availability of equipment, stability of infrastructure, and cost of apps or equipment.

Accessibility. Accessibility was a major reason why mHealth apps were adopted and used (Wiederhold, Boyd, Sulea, Gaggioli, & Riva, 2014). Apps were housed in devices that users already carried around, making them readily and conveniently accessible to users without the need for external devices (Ahtinen et al., 2013; Kuhn et al., 2014).

Accessibility to mHealth apps was not equal across populations, because there were people who had not yet crossed the digital divide. Users who concurrently used computers or touchscreen devices found apps more usable than those who did not own such devices

(Grindrod et al., 2014). Users who were given mobile devices were usually quick to get over the learning curve, tending to prefer electronic devices to paper-based methods of health data collection (Bravo, O'Donoghue, Kaplan, Luce, & Ozanne, 2014; Eskenazi et al., 2014; King et al., 2014). A notable exception was lesser-educated users who worried they might not be offered appropriate instruction to learn how to use a mobile device (Bravo et al., 2014). Users who were less educated tended to use the app less than those who were more educated (Zeng, Vilardaga, Heffner, Mull, & Bricker, 2015).

Contextual barriers such as accessibility to, and the stability of, mobile technologies still existed in less technologically developed areas. It was advised that apps in rural areas allow storing of data on the mobile device's local memory, as internet access and technological infrastructure might yet be unstable in some areas (Anderson, Henner, & Burkey, 2013). It is worth remembering that mobile broadband subscriptions in the least-developed countries currently reach only about a fifth (22.3%) of their populations (ITU, 2018). It is possible that such individual and contextual differences could hinder the uptake of mHealth apps designed for mass appeal, particularly for those residing in low resource environments (Author, 2013).

Usability. Usability issues can sometimes pose a barrier to productive use (Patel, Green, Shahzad, & Larkin, 2015). Findings related to input factors dwelled on how apps should be designed with the target audience in mind, noting their limitations and preferences during the user input phase in the app design process. Users generally preferred larger fonts, clearer color contrasts, intuitive scrollbars and buttons (Scheibe, Reichelt, Bellmann, & Kirch, 2015). Apps targeted at specific segments needed to consider user preferences. For example, teens specifically preferred “fun graphics, bold colors, and bubbly or cool fonts” (Schneider et al., 2016, p. 173). Young people felt that “content should be made fun and interactive through the use of pictures, music, videos and games” (Kenny, Dooley, &

Fitzgerald, 2016, p. 270). Adolescents were more motivated to use an app if there was a game component included (Boushey et al., 2015).

Data quality and privacy. For mHealth app content in general, those that were immersive received more positive feedback (Direito et al., 2015), and those that were more engaging attracted more users (Bricker et al., 2014). Reminders and prompts from the app were features that helped users keep engaged with the app (Ahtinen et al., 2013; Boushey et al., 2015; Giroux, Bacon, King, Dulin, & Gonzalez, 2014). Lastly, privacy and confidentiality of users' data was also of importance, particularly for mental health apps (Kenny et al., 2016).

Mechanisms

Theoretical mechanisms that explicated information and communication processes between users, designers, healthcare professionals, and the technical system were seldom explored in studies. Only a fifth (19%; $n = 16$) of the papers used theories to explain and understand the mechanisms that motivated consumers to adopt the app and adhere to usage, and explained their preferences in selection. The adherence mechanism, why users maintained app usage, and whether they follow instructions, was most commonly studied ($n = 9$). Motivational and behavioral change theories were often applied to explain why app usage could lead to certain outcomes. The adoption mechanism came next, with four papers explaining why users would adopt an app. The preference mechanism was least studied, with only two papers on why users preferred an app to other apps, or to other methods of health management.

Adoption. Papers that studied adoption mechanisms used the technology acceptance model as a theoretical explanation (Anderson et al., 2013; Patel et al., 2015; Scheibe et al., 2015). Perceived ease of use and perceived usefulness significantly affected users' intention

to use the app (Jeon & Park, 2015). Correspondingly, the lack of perceived ease of use and perceived benefits impeded adoption of the app (Scheibe et al., 2015).

Adherence. Researchers used theories and models like the supportive accountability model to study continued use and compliance. When app users were held accountable to another human (e.g., healthcare practitioner), facilitated by the app, benefits such as better communication, process accountability, and performance monitoring framework arose (Barnett et al., 2015).

Motivations. Mechanisms that led to behavioral changes in users were explained with psychological health behavior change theories. Evaluating an app built on wellness motivation theory yielded positive results relating to the constructs (McMahon, Vankipuram, Hekler, & Fleury, 2014). Similarly, an intervention strategy based on the COM-B theory of behavior change had the potential to transform healthcare models. Despite high acceptability, however, actual transformation was limited because of a lack of the input factor of accessibility (Praveen et al., 2014).

The trans-theoretical model of behavior change found that positive social inclusion and external monitoring components of an app were the most effective strategies for social group health behavior changes (Silveira, van de Langenberg, et al., 2013). The app also made users aware of the benefits of physical activity, goal-setting, self-monitoring, participation in collaborative games, positive and negative conditioning, and performance comparison.

An app built on the health action process approach and i-change approach however did not lead to actual health behavior change, though it contributed to users' awareness and intention toward behavior change (Simons, Hampe, & Guldemon, 2013, 2014). The researchers conducted a follow-up study, finding that long-term health behaviors can benefit from health competences (Simons, Foerster, Bruck, Motiwalla, & Jonker, 2015).

Output Factors

Half the papers reviewed examined output factors (52%; $n = 44$) including behavioral outcomes, efficiency, and measurable health outcomes, yielding positive results most of the time. Behavioral outcomes such as, for example, change in exercise frequency, medicine consumption and smoking habits were most frequently reported ($n = 23$). Efficiency outcomes were mentioned in 16 papers, referring to healthcare system process-related outcomes. Examples included easing communication between the healthcare provider and patients, or saving time and money for individuals and organizations at the health system level. The least reported outcome was about individual's health status ($n = 13$), which refers to the end user's physical tangible outcomes such as heart rate measurements, blood glucose level, and so forth.

Process efficiencies. mHealth apps helped in process efficiencies in two major channels; between healthcare provider and patient, and amongst healthcare providers. Mobile translation tools helped ease communication between healthcare providers and foreign-language patients (Albrecht, Behrends, Matthies, & von Jan, 2013). Data collection apps (e.g., electronic forms) saved paper for the organization, and patients found it less tedious than, and preferable to, paper forms (Bravo et al., 2014; Knoble & Bhusal, 2015). Diagnostic apps helped non-medical healthcare workers or patients to identify symptoms and possible diagnosis accurately (Grindrod et al., 2014; Larrosa et al., 2015; Pan, Dhall, Lieberman, & Petitti, 2015; Patterson, Singh, Rajbhandari, & Vishnubhatla, 2015). There was a significantly higher compliance rate for data collection via an app vs. a web-browser interface (Schreier et al., 2012).

Similarly, field workers preferred using apps to paper for recording data, for communication and coordination between different locations. For example, an app was used to monitor the spraying of pesticides for malaria control in South Africa through GPS locations and time/date stamps, with increased efficiency (Eskenazi et al., 2014). Mobile

forms saved time, reduced discrepancies and were considered more accurate (Palermo et al., 2014).

On the other hand, less positive impact was encountered if mHealth apps were not well developed, or when users were less adept with mobile technologies. Physicians found it hard to share information with patients if the information was not in the desired format, preferring graphical and video formats to enhance the process of educating patients (Anderson et al., 2013). Apps could also interfere with work processes or be less effective when users were unaccustomed to mobile technology (Eskenazi et al., 2014; Kaphle, Chaturvedi, Chaudhuri, Krishnan, & Lesh, 2015).

Individual behavior and health indicators. Users of mHealth apps generally showed improvement in health knowledge, attitudes, and behavior, although these findings were not universally applicable. In one case, health behaviors improved not only after 1 and 3 months of app usage, but continued after 10 months, which indicated that long-term sustainable health behaviors were positively correlated with grounding in health competencies (Simons et al., 2015). In another example, pregnant women were more motivated to eat healthily after using a weight-monitoring app (Knight-Agarwal et al., 2015). Blood glucose measurement frequency improved when patients used an app to track their measurements (Cafazzo et al., 2012). Medication adherence improved with medication management apps (Mira et al., 2014). Intervention apps created to help users quit smoking and alcoholic habits were useful in changing users' behaviors or intention to change. Those who had never sought professional help before were ready to quit smoking (BinDhim, McGeechan, & Trevena, 2014). The self-awareness and tracking functions provided by an app motivated users to engage in teetotaler behavior (Giroux et al., 2014). These demonstrations provide evidence of how mHealth apps can engage users cognitively and motivate them toward better health attitudes and behaviors.

Usage of mHealth apps was also correlated with positive outcomes in health indicators, both self-reported and objectively measured. Use of mHealth apps created to reduce mental stress reported significant increase in life satisfaction and reductions in stress (Ahtinen et al., 2013; Gaggioli et al., 2014; Kuhn et al., 2014; Pramana, Parmanto, Kendall, & Silk, 2014). Controlled stress levels led to reductions in heart rate after following instructions on an app (Wiederhold et al., 2014). After using an app that promoted healthy lifestyle, users had greater increase in walking speed as compared to the control group (Silveira, van de Langenberg, et al., 2013). Intention to engage in physical activity and actual BMI had significant improvements after 6 months of app usage (Turner-McGrievy et al., 2013). An app motivated users to brush their teeth longer, and therefore improved gum health (Underwood, Birdsall, & Kay, 2015). Following improvements in health behavior, longitudinal studies were able to measure resultant health outcomes, and demonstrated that usage of mHealth apps could indeed yield positive measurable health outputs.

However, outcome impacts were inconclusive—app usage did not always result in noticeable changes. There was no difference in users' physical activity, diet, and HbA_{1c} levels, despite implementation of a diabetic self-management app (Holmen et al., 2014). HbA_{1c} levels also showed no significant decrease for another group of diabetic patients using a mHealth app (Torbjørnsen et al., 2014). Despite these non-significant findings, we note that health indicators like HbA_{1c} levels are often difficult to change, and may take several years to stabilize (Nirantharakumar, Mohammed, Toulis, Thomas, & Narendran, 2018). An app tracking physical activity was found to be significantly effective in increasing walking trends, but not significantly effective in decreasing caloric intake of users (Rabbi et al., 2015). Contrary to expectations, use of a particular app led to significant increases in snacking behavior (van Drongelen et al., 2014). Knowledge of sexually transmitted diseases improved after usage of an app that allowed communication between doctors and teenagers, though it

did not influence their sexual behaviors (Lopez et al., 2014). Further research is needed to understand why apps sometimes led to behavior change, sometimes partially, and in other cases, had no effect or even adverse effects.

I-M-O Links

It is important to investigate the use of theory-informed interventions, particularly to identify papers linking technological inputs, healthcare outputs and theoretical mechanisms. This would allow a more holistic and thorough understanding of mHealth apps research. We found three papers that linked mechanisms and output factors, while another three studies examined the entire mHealth pathway. The six papers that covered mechanisms, output factors, and sometimes-input factors, seemed to indicate that theoretically-driven app interventions are generally effective.

With high usage of an engaging app built on the health action process approach and i-change models, users were motivated towards improved health behaviors (Simons et al., 2015). SmartQuit, an app built on the features of acceptance and commitment therapy, had engaging content, was more frequently used, and resulted in higher quit rates than the control (Bricker et al., 2014). Indeed, further investigation revealed that the in-app features of acceptance and commitment therapy and cognitive behavioral therapy were associated with smoking abstinence (Heffner, Vilardaga, Mercer, Kientz, & Bricker, 2015).

Of the remaining papers, 30 covered only input and output factors with explanatory theoretical mechanisms linked these factors, and nine papers covered input factors and mechanisms without testing any actual outputs. Finally, 39 papers individually covered input factors, mechanisms, or output factors. Refer to Table 1 for more details.

Discussion

As mHealth apps become increasingly popular, it is important to take stock of the literature presently available in terms of health impact, and the factors which contribute to

this effectiveness. One objective of this review study was to examine the priorities of mHealth app research, reviewing the literature for focus on technological inputs, theoretical mechanisms, and health outcomes as well as system outputs. Addressing this issue of research priorities, we found that most papers focused on technological input factors (87%), and about half on output factors (52%) such as system processes and healthcare indicators. Many studies focused on the usability of apps that are still being refined and tested, or merely on the outcomes of using that app. This focus on technical development and pilot studies reflect the nascent nature of the field of mHealth apps, with hype about the potential effectiveness out-pacing the body of evidence (Author, 2013).

With regard to theory-based mechanisms, only 19% of the papers aimed for theoretical support, favoring theories related to adoption, adherence, and preferences. Of these papers, fewer tested the effect of the theoretical aspects on the reported outcome, or used a theory to explain the reported outcomes. When theory was used, they mostly were used to describe how an app is designed or adopted, and not how the app actually works to produce health outcomes, which is more crucial to move the field forward. This shows that there is much room for more in-depth research on the theoretical investigations of how and why mHealth apps work or do not work.

Enthusiasm for the app during the study might not necessarily “translate into actual uptake, use, and recommendation” (Barnett et al., 2015, p. 113). One reason for this is possibly due to disciplinary boundaries largely proving insurmountable as conceptually comprehensive studies linking input, mechanism, and output factors were a rarity ($n = 3$). This suggests the need for focused research on theoretical explanatory mechanisms that can help us understand how tangible input factors translate into successful healthcare outputs. We propose that scholars should consider how inputs could be linked to outputs with mechanisms, so as to obtain theory-driven processes and outcomes. Iterative models for

development of adaptive treatment regimens, like the sequential, multiple assignment, randomized trial (SMART) (Almirall, Nahum-Shani, Sherwood, & Murphy, 2014) and multiphase optimization strategy (MOST) (Collins, Nahum-Shani, & Almirall, 2014), can be applied for this purpose, providing a template for developing and testing theory-driven mHealth apps.

Output factors, or effects, were studied in approximately half of the dataset, which is more than double that found in an application of the model to mHealth (in general, not apps) adoption and use in developing countries (Author, 2015). Given the growing attraction of mHealth to policymakers, healthcare professionals and practitioners in the field, the emphasis on health outcomes is both inevitable and welcome. However, though there is a general optimistic sentiment that effects are positive, this sentiment has not yet been as clearly, and as frequently, proven in empirical studies. Only 13 studies looked into the actual effects on individuals' health, with the balance examining process efficiencies in the healthcare system. There is a rise in randomized control designs in the field, suggesting that the field is maturing and will gain traction and credibility in the future with policymakers looking for rigorous forms of evidence, assuming that evidence of effective health behaviors is found.

While most papers that reported outcomes were inclined towards positive results, the research designs were not always based on control group comparisons between app usage and non-app usage. The threats to validity suggests that those findings may also be reached without the use of mHealth apps, and through other external influences. These studies typically employed the use of a questionnaire after app usage, and compared pre- and post-app usage outcomes. Manipulation of app presence and app usage should be better controlled in future studies.

mHealth appearing on the agenda for a variety of stakeholders would explain the growing techno-optimism, emphasis on results rather than theory, particularly in terms of

healthcare system efficiencies rather than on end-beneficiary health indicators. Where healthcare apps are included as a generic source of information, these prove less effective than the Internet in terms of perceived health outcomes (Bounsanga, Voss, Crum, & Hung, 2016). Combined with a preponderance of app solutions in the marketplace, low evidence of effectiveness and the lack of significant effects of the findings from RCTs are cause for concern for future research. Overall, there is mixed evidence of mHealth apps effectiveness, as demonstrated in empirical studies, with current emphasis on adoption and usage factors.

An over-riding objective was to situate the review in the traditional communication disciplines of mass, interpersonal, and human computer interaction. We find the lack of conceptual clarity led to the merger of these constructs into a 'black box', with little explanatory power to the findings (Walther, 2017). Theorists offer multiple meta-constructs to integrate the fields of mass and interpersonal communication (for review, see Kreps, 2017; Walther, 2017). At the current time, these taxonomies find considerable overlap and insufficient guidance for operationalization in the mHealth app context. Given the complexity of affordances within mHealth apps, recent studies in the journal find a plethora of processes at work, giving rise to speculation around the theoretical mechanisms operating. Project SMART, using a combination of multiple study-designed apps, email, social media, and text messages found elements of social support and social comparison processes at work, sometimes in a debilitating manner (Merchant et al., 2017). Greater specification of these differential processes was found in another study on a weight-loss app, Noom, which disaggregated the combination of peer and facilitator support, health information reading, and in-group posting and responding (Kim, Ray, & Veluscek, 2017). With these, and other studies, it would be important to see progressive iterations of the app development tested with the isolation of specific meta-constructs.

It is evident that the field of mHealth apps is embracing the complexity of technological affordances, with a rising emphasis on health outcomes, and robust research designs. Further, the rise of social influence in mHealth apps in forms ranging from healthcare provider interaction, peer support and peer competition (via gamification) requires further investigation. In conclusion, to advance the field, more robust research designs are needed to isolate and test the effectiveness of varied strategies and communication processes, and to explain theoretically the mechanisms of whether, how and why they work or do not.

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Figures

Figure 1. mHealth app review framework

Figure 2. Selection of the dataset

Figure 3. Number of papers in review framework

Table 1

Summary of Reviewed Papers

Paper (first author, year)	Name of App	App Function	Selected Input Factors	Mechanisms	Selected Output Factors
Ahtinen et al., 2013	Oiva	Self-administered preventive training of stress management skills	<ul style="list-style-type: none"> Usage: The participants used Oiva, on average, on 11.5 (SD 5.8, range 4-20) days, and there were, on average, 16.8 (SD 9.0, range 5-36) usage sessions per participant during the study. The average duration of usage sessions was 12.3 (SD 5.2, range 4.4-24) minutes. The most common place to use Oiva, reported by 80% (12/15) of participants, was at home. Typical usage contexts at home included: in bed before falling asleep or after waking up (5/15, 33% of participants), in the backyard (2/15, 13% of participants), or in the middle of household routines (3/15, 20% of participants). A typical barrier of use was being busy in everyday life (7/15, 47% of participants). Forty percent 	-	<ul style="list-style-type: none"> Behavior: Medians for each scale were 5 and statistically significantly higher than the mid-point of 4 for all the scales, improvement or maintenance of wellness ($z=2.29$, $P=.022$), learning new skills ($z=2.67$, $P=.008$), and gaining new insights ($z=2.17$, $P=.03$). The main benefit of Oiva was being able to take a break in the midst of daily hassles, whether at work or at home. Four participants (27%) reported gaining more profound benefits, such as changes in their thoughts and attitudes. Four participants (27%) also reported gaining the ability to let go of their thoughts and feelings, and change their perspective to them.

			<p>(6/15) of participants also mentioned that they forgot to use Oiva unless they consciously dedicated a time slot for it in their schedules.</p> <ul style="list-style-type: none"> • Accessibility: Ten participants (67%) brought up the ease of carrying a mobile phone along as the main benefit. Being able to open the app quickly and not requiring an extra device to carry were important benefits of the mobile phone for 27% (4/15) of participants. • Usability: Audio exercises were preferred over text by 73% (11/15) of participants because they provided guidance through the exercise. • Data Quality: Although the participants liked the current guidance in Oiva, they wished for even more guidance. Six participants (40%) would have liked a scheduled program. 		<ul style="list-style-type: none"> • Health: The change from before to after using Oiva was statistically significant for ratings of stress ($z=3.00$, $P=.003$) and life satisfaction ($z=2.32$, $P=.02$). There was no statistically significant change in psychological flexibility ($z=0.06$, $P=.950$).
Albrecht et al., 2013	xprompt-multilingual assistance	Translation for healthcare providers and patients	<ul style="list-style-type: none"> • Usage: 76% (27/36) had “rarely or never” used xprompt during the study. It was primarily used with patients (median=5, IQR=1, scale 1-6, $N=36$), but also with 	-	<ul style="list-style-type: none"> • Efficiency: Participants generally rated mobile translation tools as helpful for communicating with foreign language patients (36/39, 92%; median=5, IQR=2). They were less enthusiastic about

- at hospitals
- colleagues (median=5, IQR=2, scale 1-6; N=35).
- Accessibility: 71% (27/38) stated that the iPad was almost always available when desired; staff would have liked to have separate iPads for each nurse since it was a hassle to share a single device and to have to ask around for the device whenever it was needed.
 - Usability: xprompt was perceived to be easy-to-use (median=5, IQR=2, scale 1-7, N=36) and users did not have to spend much time to familiarize themselves with the application (median=5.5, IQR=2, scale 1-7, N=36). Some nurses stated that their problems with using xprompt and the iPads stemmed from being unfamiliar with such technology and that they had not received any introduction to the devices and the installed software. Some elderly patients had problems to use and to “get in touch” with the devices since they were unfamiliar with such technology, older members of the nursing staff

xprompt’s practical use (36/39, median=4, IQR=2.5), although the app was perceived as easy-to-use (36/39, median=6, IQR=3) and there were no obvious problems with the usability of the device (36/39, median=6, IQR=2).

were more cautious and skeptical about using the devices and xprompt. Staff also experienced problems when trying to explain the menus to foreign language patients.

- Data Quality: At times, the desired target language was not available.

Anders on et al., 2013	AFP Journal; Dermat ology; Dynam ed; Epocrat es; Medsca pe; Netter's Anatom y; UpToD ate	Informati on for clinical decisions	<ul style="list-style-type: none"> • Accessibility: An important element of a dedicated app that has particular significance for rural physicians is that dedicated apps are often configured to store some of their information locally. Internet access can be inconsistent in rural areas so having local information storage can improve access to information when it is needed. • Usability: When a dedicated app was available for a service (e.g. Epocrates has a dedicated iPad app) the other physicians were more likely to use the iPad because the apps were configured for access on a touchscreen tablet making them easier to use. • Data Quality: Study participants described 	<ul style="list-style-type: none"> • Adoption: Based on TAM, there were positive perceptions regarding adoption of the iPad technology. There was consensus that iPad device characteristics were not perceived generally as barriers to use in the clinical environment, with uniformly high ratings for size, shape, weight, heat, battery life, screen resolution and brightness, and ease of disinfection. Moderately lower scores were recorded for a few items in the barriers scale, including device ruggedness, ease of use of the virtual keyboard, and text entry errors associated with spell-checking software. The lowest item scores also showed the greatest variation, and included those 	<ul style="list-style-type: none"> • Efficiency: The physicians in this study generally felt that using graphics and video to enhance patient education would improve the education process. In most cases the information they wanted to share was not available through the iPad in a format they wanted to use.
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			Epocrates as useful for retrieving pharmaceutical information. Participants found UpToDate useful for access to current medical literature and for point-of-care information.	items associated with organizational setting. Tech support varied widely across workplace, as did workplace culture. Network connections and speed were somewhat less variable, with uniformly middling scores.	
Banos et al., 2015	mHealthApp	Data collection through external wearable devices, health promotion resource and therapy support	<ul style="list-style-type: none"> Data Quality: mHealthApp activity recognition model is not only shown to operate in an experimental basis but also proved to work well during the normal use of the system. 	-	-
Barnett et al., 2015	myPace	Consultation for weight management	<ul style="list-style-type: none"> Usage: Initial enthusiasm for the tool did not translate into actual uptake, use, and recommendation. Types of clients the dietitians perceived were most suited to the tool meant that only a small number of clients they did see were eligible to be recommended myPace. Clients may already 	<ul style="list-style-type: none"> Adherence: Based on Supportive Accountability Framework (SAF), enhanced communication, process accountability, and performance monitoring were referenced most often. 	-

			<ul style="list-style-type: none"> be using another weight management tool, for example MyFitnessPal. Accessibility: Clients had to have iPhones to use the mobile app, which further reduced the number of eligible clients, and there was reluctance to recommend the web app only as the dietitians felt it might not add much value. Usability: Flexibility of the system was particularly appealing to all the dietitians 		
BinDhi m et al., 2014	Quit Advisor	Smoking intervention	<ul style="list-style-type: none"> Usage: Total number of app downloads after one year was 1751, 72.98% (1278/1751) of them were Apple operation system users. 47.68% (835/1751) were from the United States, 29.18% (511/1751) were from the United Kingdom, and 16.68% (292/1751) were from Australia. Significant difference in stage of change between participants who looked at the five information categories, and those who did not ($P=.03$). Further logistic regression analysis controlling for age, 	-	<ul style="list-style-type: none"> Behavior: App was able to reach smokers across three countries. 77.2% (465/602) of the respondents were ready to quit in the next 30 days and the majority of these had never sought professional help (eg, "Quitline").

			gender, education, country, and time of recruitment showed that being in the “Preparation stage” or “Willing to quit in the next 30 days” were associated with looking at all the information (OR 1.7, 95% CI 1.1-2.7).		
Boushl ey et al., 2015	mFR	Diet tracking	<ul style="list-style-type: none"> • Usage: Acceptance present for majority of the 24 boys and 17 girls (n=41), but varied according to gender and eating occasion. Girls were significantly more likely than boys to capture images of their eating occasions (Fisher exact test, P=.03). Participants were more likely to take images of their breakfasts (90%, 36/40) and lunches (90%, 72/80) and least likely to capture afternoon and evening snacks, 54% (43/80) and 40% (32/80), respectively. • Usability: The image review process was found to be easy to use except for some confusion with overlapping markers on the screen. A game component would be important to increase willingness to use the mFR. 	-	-

Bravo et al., 2014	Athena	Data collection (questionnaire) on breast health at a public hospital mammography clinic	<ul style="list-style-type: none"> • Usage: The average time to complete the Athena app for all women was 16.4 minutes (range, 6.6–35 minutes). The Spanish-speaking women took longer to complete the questionnaire, averaging 24.5 minutes. • Usability: All 15 women interviewed indicated that the Athena app was easy or very easy to use, 11 preferred it to paper-based data collection. Three of the four women who did not prefer the Athena app had lower than a tenth grade education. All four women who did not prefer the Athena app were concerned that a clinic would not be able to offer the instruction necessary for them to learn how to use the device or to provide assistance while completing the questionnaire. • Data Quality: Three of the women were apprehensive regarding the security of mHealth information collected with the Athena app. One was worried about the potential for data getting mixed up with 	-	<ul style="list-style-type: none"> • Efficiency: Athena app was clearer to see, more practical, more efficient, included fewer questions, and was not as tiring as the paper version. The app would save paper.
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other respondents while another was concerned about the loss of data because she did not know how to go back and find her answers.

Bricke r et al., 2014	SmartQuit; QuitGuide	Smoking intervention	<ul style="list-style-type: none"> • Usage: SmartQuit participants opened their app 2.5 times more often than QuitGuide participants. SmartQuit participants opened their application an average of 37.2 times, as compared to 15.2 times for QuitGuide participants ($p < 0001$). • Data Quality: This suggests SmartQuit content was more engaging than Quit-Guide content. 	<ul style="list-style-type: none"> • Adherence: Acceptance and commitment therapy (ACT) is feasible to deliver by app and shows higher engagement and promising quit rates compared to an application that follows US Clinical Practice Guidelines. 	<ul style="list-style-type: none"> • Behavior: Quit rates were 13% in SmartQuit vs. 8% in QuitGuide (OR = 2.7; 95% CI = 0.8–10.3).
Cafazzo et al., 2012	bant	Diabetic data collection	<ul style="list-style-type: none"> • Usage: 161 rewards (an average of 8 rewards each, $N = 20$) were distributed to patients based on their frequency of measurement, with 50% (10/20) of patients collecting more than 10 awards, 25% (5/20) collecting fewer than 10 rewards, and 25% (5/20) collecting no rewards. 	-	<ul style="list-style-type: none"> • Behavior: Daily average frequency of blood glucose measurement increased 50% (from 2.4 to 3.6 per day, $P = .006$, $n = 12$). • Health: HbA1c did not change significantly over the pilot period (average 8.8%, SD 0.74 vs 9.2%, SD 1.03, $P = .11$).
Casper son et al., 2015	FRapp	Diet tracking	<ul style="list-style-type: none"> • Usage: Dietary intake was recorded on average for 3.2 (SD 1.3 days; 68% weekdays and 32% weekend days) with 	-	-

			<p>an average of 2.2 (SD 1.1) eating events per day per participant. A total of 143 eating events were recorded, of which 109 had at least one associated image and 34 were recorded with text only. Of the 109 eating events with images, 66 included all foods, beverages and a fiducial marker and 44 included both a pre- and post-meal image. Text was included with 78 of the captured images. Of the meals recorded, 36, 33, 35, and 39 were breakfasts, lunches, dinners, and snacks, respectively.</p> <ul style="list-style-type: none"> • Usability: Eight of 18 participants were able to follow all instructions: included pre- and post-meal images, a fiducial marker, and a text descriptor and collected diet records on 2 weekdays and 1 weekend day. 		
Clough & Casey, 2015	PsychAssist	Adjunct to face-to-face therapy for	<ul style="list-style-type: none"> • Usage: Participant completed all written therapy tasks using PsychAssist. 	-	<ul style="list-style-type: none"> • Health: Michael no longer met criteria for panic disorder, agoraphobia, or the specific phobia. He did however still meet criteria for social phobia,

		anxiety disorder			
Direito et al., 2015	Zombie s, Run; Get Runnin g	Promotin g physical activity	<ul style="list-style-type: none"> Usage: Approximately two-thirds of participants in the intervention groups reported using the app either 2 (10/32, 31%) or 3 times per week (10/32, 31%), whereas 8 of 32 (25%) only used it 1 time per week. No differences were evident on timing of use (ie, weekday, weekend, morning, afternoon, evening). Apps were mostly used outdoors (eg, street, park vs gym, home treadmill) and while alone (n=13 alone, n=7 with friend, and n=9 with family). For the app Zombies, Run!, the features mostly used by participants were the “workout mission tasks” (n=14) and “story and run log” of completed workouts (n=10), whereas social networking features (“share my runs”: n=0; “ZombieLink account”: n=3) were seldom or never used. For the app Get Running, the feature mostly used by participants was the description of the “week-runs” (n=13), 	-	<p>although at a lower severity rating than at pre-treatment.</p> <ul style="list-style-type: none"> Health: Time to complete the fitness test decreased in both app groups, but there were no statistically significant differences observed between the intervention groups and the control (immersive app group: adjusted mean difference –28.4 sec, 95% CI –66.5 to 9.8, P=.20; nonimmersive app group: adjusted mean difference –24.7 sec, 95% CI –63.5 to 14.2 sec, P=.32).

			<p>whereas only 1 participant reported using the social networking feature “status updates.</p> <ul style="list-style-type: none"> • Usability: The nonimmersive app received less positive feedback around motivational aspects (e.g. , “Using the app became too tedious”). Participants perceived the layout of the apps and menus as well structured and “straightforward” to use. Being able to receive clear instructions, listen to their own music during the training sessions, task difficulty increasing gradually, and encouragement provided were features highlighted as useful to support participants’ fitness. Some also considered it helpful if the app allowed choosing between different goals and activities. 		
Eskena zi et al., 2014	mSpray	Reportin g of indoor residual sprays for Malaria	<ul style="list-style-type: none"> • Usage: 2,865 entries recorded (99.1% had a GPS accuracy of 20 m or less). • Accessibility: Logistical and technical challenges were to blame for the majority of missed mSpray entries. A main 	-	<ul style="list-style-type: none"> • Efficiency: Data was recorded with a time/date stamp and can be provided to MCP and other data users in real time. A little over a third of users reported that mSpray made it difficult to follow the sprayers and more

challenge was that too few workers were equipped with phones. Users expressed concerns over how spray workers could manage both phones and heavy compression sprayers or how foremen could input all data while performing other essential functions. Though there were no reported problems of poor cellular coverage or upload speeds, there were issues with uncharged cell phones, cell phone failure, and exhausted data bundles.

- Usability: Learned quickly by users, well accepted and preferred to the current paper-based method. Almost all felt comfortable using mSpray within a week of using the app and none found it difficult to use. Some users expressed concerns about use of the cell phones themselves, including that the keys on the phones were too small to use easily, and that they had difficulty seeing the phone screen or reading the text due to small

than half reported that mSpray interfered with their normal work. Almost all felt mSpray was easy and fun to use and were satisfied with the app. The mSpray application has numerous advantages over the current paper-based documentation system used in South Africa and elsewhere, the most important of which is the accurate monitoring of spray events at the homestead level (GPS coordinates).

font size and glare from sunlight.

- Data Quality: The sprayer IDs in SP forms and mSpray were occasionally discordant. These were likely data entry errors attributable to a long drop-down list with similar last names.

Gaggio li et al., 2014	Positive Techno logy	Guided relaxatio n, biofeedb ack, stress tracking	<ul style="list-style-type: none"> • Usage: There were a total of 182 relaxation sessions. 	-	<ul style="list-style-type: none"> • Health: There was a significant decrease of perceived stress level ($F=15.2$; $p<.01$); a significant decrease of arousal ($F=13.7$; $p<.01$); and a significant increase of valence ($F=13.1$; $p<.01$). There was a pre-post decrease in mean heart rate values, albeit not statistically significant.
García - Gómez et al., 2014	SapoFit	Diet tracking	<ul style="list-style-type: none"> • Usability: Users strongly agree that platform has an attractive design, and a friendly and intuitive user interface. 	-	-
Garten berg et al., 2013	Proacti ve Sleep	Sleep tracking	<ul style="list-style-type: none"> • Usability: Participants were faster to enter sleep amount in the new interface condition ($M = 15.56$, $SD = 1.77$) than the old interface condition ($M = 20.88$, $SD = 1.08$), $t(16) = 2.57$, $p<.05$. Despite the fact that entering habits took longer in 	-	-

			the new interface, participants rated entering habits in the new interface as easier than the old interface. An app should be designed not only to reduce the amount of time it takes a user to input data, but also to conform to the user's mental models of its behavior.		
Giroux et al., 2014	LBMI-A	Alcoholism Intervention	<ul style="list-style-type: none"> • Usability: Participants indicated that they liked prompts that the LBMI-A provided that encouraged participants to enter their number of drinks each day or reminded them to use specific features of the phone. • Data Quality: Participants often reported that when they entered in the information they were surprised by the amount they actually drank. 	-	<ul style="list-style-type: none"> • Behavior: Participants felt that the information and practice provided by the pleasurable activities tool helped them to engage in more pleasurable activities in their daily life. Participants indicated that tracking progress allowed them to set goals for themselves and boosted their confidence when they could look back and see improvement. This process created motivation to continue engaging in nondrinking behavior because it was rewarding. Participants reported that knowing they had to enter the number of drinks they had into their phone helped create accountability for their drinking and as a result served as a deterrent.

Goh et al., 2015	iDAT	Diet tracking, physical activity tracking	<ul style="list-style-type: none"> Usage: There were Minimal Users (66 out of 84 patients, 78.6%, with either no iDAT use at all or use only in the first 2 weeks), Intermittent-Waning Users (10 out of 84 patients, 11.9%, with occasional weekly use mainly in the first 4 weeks), and Consistent Users (8 out of 84 patients, 9.5%, with weekly use throughout all or most of the 8 weeks). 	<ul style="list-style-type: none"> Adherence: The adjusted odds ratio of being a Consistent User, relative to a Minimal User, was significantly higher for females (OR 19.55, 95% CI 1.78- 215.42) and for those with higher exercise motivation scores at baseline (OR 4.89, 95% CI 1.80-13.28). The adjusted odds ratio of being an Intermittent-Waning User relative to a Minimal User was also significantly higher for those with higher exercise motivation scores at baseline (OR 1.82, 95% CI 1.00- 3.32). 	-
Goldstein et al., 2014	iRx Reminder	Medication adherence tracking	<ul style="list-style-type: none"> Usability: All participants with the m-health device demonstrated their ability to use the smartphone application. In both conditions (reminding or passive), participants preferred the m-health intervention to the telehealth intervention ($P < 0.001$). Participants who received smartphones with the m-health app (mean score 48.7) rated their device significantly higher on patient acceptance and device helpfulness ($P < 0.001$) than people who 	-	<ul style="list-style-type: none"> Behavior: Device type was not significantly associated with medication adherence ($P = 0.87$). In addition, condition was not significantly associated with medication adherence ($P = 0.48$). There was no significant interaction between device and condition ($P = 0.33$). The overall adherence rate for both devices and conditions was 78% (SD 35). People with the telehealth device adhered 80% of the time and people with the smartphone adhered 76% of the time. Those

received telehealth medication containers (mean score 33.4).

who received reminders adhered 79% of the time, and those with passive medication reminder devices adhered 78% of the time.

Grindrod et al., 2014	ClereMed	Identify individuals who have difficulty reading or understanding medication labels	<ul style="list-style-type: none"> • Accessibility: 32% (15/47) of participants did not use a computer, tablet, e-reader, or mobile phone at home. Participants who had access to a computer or touchscreen device at home completed ClereMed in a mean time of 26 (SD 16) seconds, compared with 52 (SD 34) seconds for those who did not ($P=.001$). • Usability: The mean SUS was 76/100 (Table 2), with 84% (37/44) of participants agreeing the app was easy. Participants who owned computers or touchscreen devices found ClereMed to be more usable than those who did not own a computer or touchscreen (mean SUS score difference 16.22, 95% CI 11.59-20.86, $P<.03$) The difference may be largely attributable to the learnability of ClereMed (items 4 and 10), with 60% (9/15) of those with no technology ownership 	-	<ul style="list-style-type: none"> • Efficiency: ClereMed correctly identified 71% (5/7, sensitivity) of participants who had functional vision impairment and 86% (31/36, specificity) who had healthy, functional vision. Compared with the real-life prescription vial simulation, ClereMed correctly identified 63% (5/8) of people who could not complete the simulation and 97% (34/35) of participants who could complete it.
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agreeing or strongly agreeing they would require some kind of technical support to get through it (SUS Factor 4) and 47% (7/15) agreeing or strongly agreeing they needed to learn a lot before using ClereMed (SUS Factor 10), compared with a respective 24% (7/29) and 17% (5/29) in the technology ownership group.

Some positive comments included that the screen was a nice size, the app had good contrast, instructions for the simulation activity were clear, and the process was quick and concise. Of participants who found the app difficult to use, many had trouble navigating the touchscreen, either due to lack of dexterity, hand tremor, or simply because the screen did not respond to their touch.

- Data Quality: ClereMed correctly identified 72% (5/7) of participants with functional reading difficulty, and 63% (5/8) who failed a real-life pill-sorting task, but only 21%

				(6/28) of participants with cognitive impairment.		
Heffner et al, 2015	SmartQuit	Smoking intervention	-		<ul style="list-style-type: none"> • Preferences: Eight out of the top 10 most popular features were based on traditional CBT: developing a quit plan (#1), tracking (tracking smoking, #2; viewing locations of tracking, #7); viewing progress (in calendar form, #3; in chart form, #5; in the form of badges earned, #9), sharing (#4), and journaling (opening notes, #10). The only two ACT-specific features represented in the top 10 list were tracking practice of letting an urge pass (#6) and viewing an ACT exercise for staying motivated (#8). • Behavior: App features that demonstrated the strongest prospective prediction of smoking abstinence: Two of the features were ACT-specific tracking features – i.e. tracking ACT skills practice (p 1/4 0.01) and practice of letting urges pass (p 1/4 0.03) – whereas viewing the quit plan (p1/40.03) was a traditional CBT feature. Only one baseline variable was associated with use of one of these features as well as well as smoking abstinence – male gender predicted greater use of the tracking ACT skills practice exercise (p1/40.02) as well as abstinence (p1/40.02). Controlling for gender did not change conclusions about the relationship between tracking ACT skills practice and smoking abstinence (p 1/4 0.009, OR 1/4 18.8, 95% CI 1/4 2.1–171.3). 	
Helander et	The Eatery	Photographic dietary	• Usage: Overall adherence was low—only 2.58% (4895/189,770) used the app	-	<ul style="list-style-type: none"> • Behavior: Actives used the app for a longer time and did dietary self-monitoring more 	

al., 2014	self- monitori ng and peer feedback	actively. The day of week and time of day the app was initially used was associated with adherence, where 20.28% (5237/25,820) of users had started using the app during the daytime on weekdays, in comparison to 15.34% (24,718/161,113) of dropouts. Users with strict diets were more likely to be active (14.31%, 900/6291) than those who had not defined any diet (3.99%, 742/18,590), said they ate everything (9.47%, 3040/32,090), or reported some other diet (11.85%, 213/1798) ($\chi^2_3=826.6$, $P<.001$).	frequently. Users with strict diets had higher healthiness scores than users in other dietary preference categories and they also had the highest proportion of improvers.
Holme n et al., 2014	Few Touch Applica tion	Diabetic self- manage ment	<ul style="list-style-type: none"> Usage: In the FTA group, 39% were substantial users of the app; 34% of the FTA-health counseling (HC) group were substantial users. Those aged ≥ 63 years used the app more than their younger counterparts did (OR 2.7; 95% CI 1.02-7.12; $P=.045$). Behavior: There were no significant differences between the groups (FTA, FTA-HC, control) in self-reported levels of physical activity (inactive to active or opposite). The changes in the intake of fruits and vegetables, meat, chocolate, and fish after 1 year did not differ between the 3 groups. Health: None of the clinical variables differed significantly between groups at baseline.

However, a higher proportion of persons in the control group reported depressive symptoms compared with the other 2 groups. The change in HbA1c level did not differ significantly between the 3 groups after 1 year. Body weight was slightly reduced in all 3 groups at the 1-year follow-up, although not significant. Mean change in skill and technique acquisition was significantly higher in the FTA-HC group.

Hong et al., 2014	iCanFit	Physical activity tracking	<ul style="list-style-type: none"> Usability: Participants completed all 15 tasks on the iCanFit site in an average of 31 (SD 6.9) minutes; some tasks required more time or needed assistance. In the user-experience survey, participants reported high levels of usefulness and satisfaction. More than 56% (13/23) of participants indicated they would continue using the program and recommend it to their families or friends. 	-	-
Jaensson et al., 2015	RAPP	Postoperative recovery	<ul style="list-style-type: none"> Usability: There were four patients that reported that the background color was an issue 	-	-

		monitoring	<p>and three patients had comments about the text size.</p> <ul style="list-style-type: none"> • Data Quality: All ten patients expressed a positive attitude toward the method of evaluating postoperative recovery using an app. Staff found the questions in the SwQoR relevant, and they also confirmed the need for systematic follow-up in the recovery process. 		
Jeon & Park, 2015a	Obesity Care	Weight self-management	<ul style="list-style-type: none"> • Usability: In heuristics tests, 57 comments were made, and the mean usability score was 3.47 out of 5. Thirteen usability problems were identified by the heuristics and usability evaluations. Of the higher-level categories, system usefulness and information quality received the highest score (20.9 for each), and interface quality received the lowest score (10.1). 	-	-
Jeon & Park, 2015b	Obesity Care	Weight self-management	<ul style="list-style-type: none"> • Usage: The frequency was highest for diet recordings, at 17.9 ± 26.13 (range, 0–102), and lowest for exercise recordings, at 4.3 ± 9.89. 	<ul style="list-style-type: none"> • Adoption: Factors influencing mobile obesity-management app acceptance using a TAM (MHS acceptance model); compatibility, perceived usefulness, and perceived ease 	-

of use significantly affected the behavioral intention to use the mobile obesity-management app. Technical support and training also significantly affected the perceived ease of use; however, the hypotheses that self-efficacy affects perceived usefulness and perceived ease of use were not supported in this study. Mean values for compatibility, self-efficacy, and technical support and training were 3.17, 2.57, and 3.98, respectively. The mean values for PEOU and PU were 3.44 and 2.95, respectively, and the mean BI for the mobile obesity-management app was 3.20.

Jonassaint et al., 2015	SMART	Sickle cell disease monitoring and self-management	<ul style="list-style-type: none"> Usage: Patients had recorded on SMART for a median of 32 days (range 5 to 164). Patients were compliant, making at least one SMART entry per day, 18 of 28 days (64.5%) on average (Table 3). Daily compliance with SMART entries was a mean 75.0%, with a high of 85.7% in week 1 and low of 57.9% in week 4; however, one-third (n 1/4 5) of 	-	-
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			<p>the patients were 100.0% compliant even in week 4. Patients who were over age 35 or used an iPad for the study had the highest compliance rates.</p> <ul style="list-style-type: none"> • Data Quality: There was a high intraclass correlation between pain measurements entered on the paper VAS and SMART on the iPhone and the iPad. 		
Kalz et al., 2014	(13 apps)	Cardiopulmonary resuscitation (CPR) training and real incident support	<ul style="list-style-type: none"> • Usability: Only five apps have a usability score above average (SUS>68) and fall into the percentile rank of above 50%. Most apps with high usability also have high learnability. 	-	-
Kaphle et al., 2015	CommCare	Maternal and newborn care	<ul style="list-style-type: none"> • Usability: Age affected CommCare user type negatively, with an increase in age increasing the likelihood of belonging to a lower category of CommCare adoption (-0.105, P=.08). Other individual characteristics did not affect adoption or the predicted values estimating the relationship between adoption and quality and experience of 	-	<ul style="list-style-type: none"> • Efficiency: The quality score for high users of CommCare was higher by 33.4% (P=.04), on average, compared to low users of CommCare. Those who scored higher on CommCare proficiency also provided significantly higher quality and experience of care, where an additional point in CommCare proficiency score increased the quality score by

			care, although illiteracy was able to affect the relationship negatively.			around half a point (0.541, $P=.07$), and experience score by around a third of a point (0.308, $P=.03$).
Kenny et al., 2016	CopeSmart	Self-monitoring of moods	<ul style="list-style-type: none"> • Accessibility: Important to use appropriate language to ensure any information provided is accessible to young people. Emphasis was placed on the importance of apps being free of cost and participants highlighted that if there is a charge for these apps, young people will not use them. • Data Quality: Young people highlighted that mental health apps must be safe to use in terms of confidentiality, cyber-bullying and stigma. They reported that apps should be password protected and user control over privacy should be incorporated so users can choose whether they want to share their personal information or keep it private or anonymous. Participants emphasised that mental health apps must be engaging and that information presented via apps should be concise and to the point. 	-	-	

King et al., 2014	Comm Care, ODK Collect, MIVA	Electronic data capture	<ul style="list-style-type: none"> • Accessibility: ODK Collect is preferable in areas of poor Internet connectivity as the whole process from form development to data download can be done offline, and is well suited to cross-sectional surveys. • Usability: All fieldworkers preferred EDC to paper-based systems, one commenting that carrying paper-based systems can be tiresome, whereas the EDC is easier to carry, control, and work with. Despite the majority of fieldworkers never having used a smartphone or PDA previously, most became competent quickly, and an initial lack of familiarity does not seem to have been a barrier to adopting an EDC system. • Data Quality: Fieldworkers liked the integrated skip patterns as it simplified their interviews, and also reduced the amount of data cleaning required. Fieldworkers also commented on the ability to take photographs and videos as a positive feature in CommCare and ODK Collect. 	-	-
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Kizakevich et al., 2014	PHIT for Duty	Self-assessment and self-help for moderate psychological health problems	<ul style="list-style-type: none"> Usability: Average System Usability Scale (SUS) score reported by these nine participants was 85 ± 12 (mean$\pm$sd). The percentile rank for this average score is 95%, meaning that the usability of the near-final PHIT for Duty system exceeds 95% of all products tested using the SUS. 	-	-
Knight - Agarwal et al., 2015	Eating4two	Weight monitoring	<ul style="list-style-type: none"> Usability: 70% (n=7) of participants reported finding the app a helpful tool to graph and monitor their weight change, 20% (n=2) found it neither helpful nor unhelpful, and 10% (n=1) found it unhelpful (mean=3.6; median=4). Women reported that they would have liked scales or other markers on the graph to demonstrate exact weight gain and that the nutrition information should be formatted in a more user friendly way. Data Quality: 0% (n=1) of participants reported finding the nutrition information contained in the app very helpful, 50% (n=5) found it helpful, 30% (n=3) neither 	-	<ul style="list-style-type: none"> Behavior: Women expressed motivation to stay healthy during pregnancy. TheEating4Two app was viewed by the majority of participants as a support system to help motivate healthy behaviors during pregnancy and as a credible resource for accessing information.

			helpful nor unhelpful, and 10% (n=1) found it unhelpful (mean=3.6; median=4).		
Knoble & Bhusal, 2015	e-algo	Clinical decision support	<ul style="list-style-type: none"> • Usage: Reasons for non-use were that they were too busy and the study logging and questionnaires took too much time. E-algo use dropped significantly once the compulsory phase ended. • Usability: Initially, they stated some difficulty in learning how to navigate the application but after a few days of practice, the HCWs found the device easy to use. Perception of time-taking was the primary factor that impacted its use. They requested short-cuts to key features. • Data Quality: HCWs stated that patients had confidence that the “computer” would give the correct diagnosis. They stated that it improved their decision-making and enabled them to view a full differential diagnosis for a specific complaint. They saw the tablet having a dual purpose: learning as well as diagnosis. Certain 	-	<ul style="list-style-type: none"> • Efficiency: Patients expressed confidence in the electronic device and stated that that was their preference.

common chief complaints were missing from the application.					
Kuhn et al., 2014	PTSD Coach	PTSD self-management	<ul style="list-style-type: none"> • Usage: scheduled specific times to use PTSD Coach (set alarm), used the app at night or to help them with sleep problems. • Accessibility: Participants consistently noted that they liked having the app on a mobile device as it was convenient, easy to carry, and available at any time. • Usability: Interface was simple to use, readily accessible, would appeal to technology novices (including older individuals), afforded customization (e.g., integrating one's own music), and incorporated specific features that they found attractive. • Data Quality: PTSD Coach improved their knowledge about PTSD and was a good reference. 	-	<ul style="list-style-type: none"> • Health: Using PTSD Coach reduced distress and PTSD symptoms. Majority of participants (i.e., 68–91%) endorsed the app as moderately to extremely helpful achieving its intended purposes (e.g., learning about PTSD symptoms, finding effective ways to manage symptoms).
Landman et al., 2015	CliniCam	Collect photos for electronic health records	<ul style="list-style-type: none"> • Usage: Approximately half of the respondents (53%) did not use CliniCam, many noting that they did not have a patient requiring photos during this time. 	-	-

			<p>89% found it useful or very useful for clinical practice and easy to use, and wanted to continue using the app.</p> <ul style="list-style-type: none"> • Accessibility: CliniCam is designed to work only on the hospital's secure WiFi network. Investigation of the slowness and lost photos revealed users were often connecting to other networks and that some clinical areas did not have adequate WiFi signals. Some users experienced difficulty with WiFi connectivity which was addressed by enhancing CliniCam to check for connectivity on launch. • Usability: Several respondents reported that the app was slow and one respondent reported losing a photo. 		
Lane et al., 2014	BeWell +	Monitoring and promoting holistic wellbeing (sleep, activity, social	<ul style="list-style-type: none"> • Usability: Subjects that have access to multi-dimensional feedback on the phone are better able to connect life events to fluctuations in wellbeing. On average multi-dimensional group recalls 4.28 events per week compared to 	-	<ul style="list-style-type: none"> • Behavior: Users can digest multi-dimensional BeWell+ feedback and are seen to make positive changes in their behavior.

		interaction)	<ul style="list-style-type: none"> just 1.8 events for baseline group. Data Quality: BeWell+ can accurately track wellbeing across multiple behavioral dimensions. We find 70 % of subjects believe that BeWell+ is a helpful and enjoyable app. A common theme with subjects is that they are surprised by what they learn from the study about their lifestyles. 		
Larrosa et al., 2015	AudCal	Hearing handicap calculation	-	-	<ul style="list-style-type: none"> Efficiency: The mean difference between AudCal and standard audiogram thresholds was 0.21 ± 6.38 dB HL. Excellent reliability and concordance between standard audiometry and the application's hearing loss assessment test were obtained (Cronbach's alpha = 0.96; intra-class correlation coefficient = 0.93). AudCal vs a web-based calculator were perfectly correlated (Pearson's $r = 1$).
Lim et al., 2015	PotM	Clinical evaluation for hypertensive	<ul style="list-style-type: none"> Usability: Users found keys too small, causing them to keep pressing the wrong buttons. Users felt the wheels were too sensitive, and did not 	-	-

		pregnant women	understand how to change the numbers on the wheels.		
Lopez et al., 2014	Doctor Chat Mobile	Education and information on sexuality	<ul style="list-style-type: none"> • Usage: 48 of them (83%) consulted 1 to 3 times. Of 58 subjects, 9 of them (16%) made 4 or more consultations, and 1 person (2%) made 29 consultations • Accessibility: 92.3% (131/142) of them considered having access to a mobile-based teleconsultation tool on sexual health to be important or very important • Usability: 69.7% (99/142) of them considered the use of the app to be easy or very easy, in contrast with the remaining 30.3% (43/142) that found the app difficult or not so easy to use. 	-	<ul style="list-style-type: none"> • Behavior: Use of the tool did not influence sexual practice. Other indicators, such as those concerning knowledge of the symptoms of sexually transmitted infections, seemed to improve with the intervention.
Losa-Iglesias et al., 2016	Heart Rate Plus	Heart rate measurement	<ul style="list-style-type: none"> • Data Quality: There was a significant correlation coefficients and no systematic differences between radial pulse palpation and pulse oximeter and a high precision. App demonstrated high reliability and consistency between systems with respect to the heart rate parameter of 	-	-

			healthy adults using three systems.		
Luxton et al., 2012	FaceTime	Video call for telemental health	<ul style="list-style-type: none"> • Accessibility: There is a question of feasibility of using smartphones when network connectivity is less than optimal. • Usability: All of the testers indicated that the size of the video screen was adequate, and none of the testers indicated that use of the video feature made him or her feel dizzy or nauseated. 	-	-
Martinez-Perez et al., 2015	Heartkeeper	Cardiac self-management	-	<ul style="list-style-type: none"> • Preferences: The average scores obtained for were good, which is an indicator of the satisfactory Quality of Experience (QoE) that Heartkeeper provides to its users. QoE of mobile apps are very useful for developers in order to find and improve the aspects that needs enhancements according to the feedback obtained. 	-
Mattson, 2015	Art Therapy Draw!	Art therapy for mental health	<ul style="list-style-type: none"> • Usage: Expert users commented that the app would likely be suitable for use with disabled persons or those 	-	-

			allergic to conventional art materials.	
			<ul style="list-style-type: none"> • Usability: Layout of the app proved easy to navigate and required little knowledge to operate. 	
McMahon et al., 2014	Ready ~Steady	Self-management for fall prevention	<ul style="list-style-type: none"> • Usage: Four participants wore an iPod touch® for 8–12 h daily over the course of 4–7 days (mean = 5), consistent with estimates of a “valid” days based on accelerometer data. • Usability: Most participants felt anyone could learn to use the app; two suggested that learning curves would vary in length. Suggestions for improving app instructions included providing 1:1 instruction with demonstration and return demonstration on charging the device and activating the app, as well as incorporating illustrations into written instructions. • Data Quality: Two participants commented that the information they received from the app about physical activity behavior was more helpful than they expected. They found 	<ul style="list-style-type: none"> • Adherence: Ten of the statements elicited overall positive responses to clarity, homogeneity, and correspondence to Wellness Motivation Theory (WMT) constructs, with mean ratings ranging from 3.3 to 4.78. Relevance of two motivational statements ranged from not at all relevant (1) to very relevant (5) with an average of 3.1.

			<p>themselves checking the app frequently and adjusting their activity accordingly. In contrast, two other participants commented that they were not sure if the information on the interface display would be “valuable,” and that they may not wear it in certain locations, such as church.</p>		
Min et al., 2014	Pit-a-Pat	Data collection for breast cancer patients	<ul style="list-style-type: none"> Usage: The median value of individual patient-level reporting rates was 41.1% (range 6.7-95.6%). The longitudinal day-level compliance curve fell to 50.0% at day 34 and reached a nadir of 13.3% at day 90. The cumulative longitudinal compliance curve exhibited a steady decrease by about 50% at day 70 and continued to fall to 45% on day 90. Women without any form of employment exhibited the higher compliance rate. 	-	-
Mira et al., 2014	ALICE	Self-management for medication	<ul style="list-style-type: none"> Usage: Rates of missed doses and of medication errors, and adherence to treatment measured by the 4-item Morisky Medication Adherence Scale (MMAS- 4) 	-	<ul style="list-style-type: none"> Behavior: Patients in the experimental group obtained better MMAS-4 scores ($P<.001$) and reported fewer missed doses of medication ($P=.02$). ALICE only helped to

					significantly reduce medication errors in patients with an initially higher rate of errors ($P<.001$). Patients with no experience with information and communication technologies reported better adherence ($P<.001$), fewer missed doses ($P<.001$), and fewer medication errors ($P=.02$).
Mirkovic et al., 2014	Connect Mobile	Cancer patient-provider communication	<ul style="list-style-type: none"> Usability: 27 design issues (13 for mobile apps and 14 for tablet apps) were mapped to source events (i.e., errors, requests for help, participants' concurrent feedback, and moderator observation). Majority of violations were related to enabling ease of input, screen readability, and glanceability (15 issues), as well as supporting an appropriate match between systems and the real world (7 issues) and consistent mapping of system functions and interactions (4 issues). 	-	-
Monney et al., 2015	Stop-cannabis	Cannabis self-management	<ul style="list-style-type: none"> Usage: Used at least weekly by most participants, daily by more than 70%, and several 	-	<ul style="list-style-type: none"> Behavior: More than 80% of participants (397) considered the app to have helped them “a

			<p>times a day by half of the participants.</p> <ul style="list-style-type: none"> • Usability: Most of the open comments by users were related to the text content of the app, asking for more personalized messages, longer support time, and more personalized content. Such aspects should be considered for future developments of this app. • Data Quality: More than 80% of the participants found the app messages “helpful” or “very helpful.” 		<p>little” or “a lot” to stop or reduce cannabis consumption.</p>
O'Malley et al., 2014	Reactive	Weight self-management	<ul style="list-style-type: none"> • Usability: A global SUMI score of 64 was promising as 50 is an average score and 68% of software falls within one standard deviation of the mean (ie, scores between 40 and 60) on the SUMI. All tasks were completed successfully and users commented on how easy the interface was to navigate. Noncritical errors recorded included difficulty in recognizing what the app icons represented (5 participants) and difficulty with reading the text on the app at times (2 	-	-

participants). Participants commented that improvements were needed so that the app could run on an iPhone (n=1); that the colors could be brighter (n=3), and that the text could be larger (n=2).

Palermo et al., 2014	Victorian Healthy Food Basket	Food cost monitoring for dieting	<ul style="list-style-type: none"> • Usability: App was easy to use and they were able to be familiar with the available functionality quickly and with minimal training. Participants commented that having access to the data collection rules in the iPad reduced the need to manage multiple sheets of paper. Field workers recorded that the time taken to collect and upload data was between 45-60 minutes. 	-	<ul style="list-style-type: none"> • Efficiency: Field workers commented that the iPad app resulted in more accurate data collection with fewer discrepancies. Collecting data in a paper format at the store and entering the data later into an excel file was tedious, error prone, and time-consuming. The field workers reported that another significant benefit of portable digital device was the time savings made. Compared to the previous paper-based model, field workers found the ability to upload the data directly from the app saved time. Compared to paper-based data collection, using the iPad app was reported to be a fast, easy, and convenient way to collect data whilst in the supermarkets.
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Pan et al., 2015	PD Dr	Data collection & self-assessment for Parkinson's disease	<ul style="list-style-type: none"> Usability: The system is simple to use, user friendly, and economically affordable. 	-	<ul style="list-style-type: none"> Efficiency: PD Dr could effectively capture important motion features that differentiate Parkinson's disease severity and identify critical symptoms. For hand resting tremor detection, the sensitivity was .77 and accuracy was .82. For gait difficulty detection, the sensitivity was .89 and accuracy was .81.
Parma et al., 2013	iMHere	Self-care and patient-clinician communication for chronic diseases	<ul style="list-style-type: none"> Usage: There were 5 patients who used all the app features, 3 patients used all except 1 of the app features, while 4 patients used only 3 app features. We observed that the daily usage increased significantly in the first 2 months (from approximately 1.3 times a day to over 3 times a day). This is consistent with how patients began using the apps. Not all apps were in full use until the second month because the patients were trained one app at a time until it was being utilized properly in the first month. The usage did plateau after 2 months, at around 3.5 times a day per patient. 	-	-

- Usability: Due to the narrow width of the scrollbar, it was not obvious to the patients that they needed to scroll down, leading to under-completion of the data. Related to this problem was the fact that the green “+” button, used throughout the app suite to add items such as new schedules, also required patients to scroll down the screen to use it. Another issue was found with the Skincare app, where an on-screen button was used for taking wound pictures. This button was difficult to use for patients attempting to photograph a wound on a less accessible area of their body. Instead of using an on-screen button to take the picture, patients could more easily utilize the physical control button on the device that is already built in to perform this function. We also found minor issues related to the use of a light text color on top of a grey background making text difficult to read; also an activity button at the top of the

			screen was too small for some users to access.		
Patel et al., 2015	UpToDate	Clinical decision support	<ul style="list-style-type: none"> Usage: Five JDs made 14 or more recorded interactions. This equates to 90.1% of all observed interactions (n=128). Seven JDs did not use the mCDS software. The JD who interacted the most made 43 interactions, equating to 11 interactions/month. The mean number of interactions across the JDs who used mCDS (excluding those who did not interact at all) was 4 interactions/month. a greater proportion of interactions are conducted off-shift. Usability: Usability issues were a barrier to mCDS use in this study. This supports the findings from other studies in general workplace settings including health care, which have identified screen size as a particular issue for end users. 	<ul style="list-style-type: none"> Adoption: Based on technological Acceptance Model. Perceived ease of use cited twice, perceived usefulness cited three times. 	-
Patterson et al., 2015	Epilepsy Diagnosis Aid	Diagnostic questionnaire for epilepsy	<ul style="list-style-type: none"> Usability: The app was easy to use with little training and took about 5 minutes to administer. 	-	<ul style="list-style-type: none"> Efficiency: There was good agreement between the app score and the neurologists' diagnoses (weighted kappa = 75.3%).

Ploder e et al., 2014	Distract Me	Smoking intervention	<ul style="list-style-type: none"> Usage: Participants consumed on average 22.1 tips (range, 0-68) and 16.4 distractions (range, 1-69). Whereas they posted more distractions than tips (mean, 2.3; range, 0-12 distractions, and mean, 1.5; range, 0-5 tips), they posted more comments on tips (mean, 1.6; range, 0-5) than on distractions (mean, 1.0; range, 0-5). Data Quality: Some participants were concerned that the content in DistractMe was mostly not interactive enough and this allowed them to smoke while using the app. 	-	-
Pramana et al., 2014	SmartCAT	Anxiety disorder intervention	<ul style="list-style-type: none"> Usage: The data from patient use revealed that the app was used frequently during treatment. The app was used more frequently during the first week, and usage leveled off toward the end. The high usage frequency during the first week might reflect the fact that patients were becoming familiar with the app by self-initiating the skills coach entries several times. 	-	<ul style="list-style-type: none"> Behavior: SmartCAT was found to be capable of supporting BCBT for child anxiety and received positive feedback from both therapists and youth patients.

			<ul style="list-style-type: none"> Usability: Patients rated the app as highly usable (mean = 1.7 on a 1–7 scale, with 1 = “easy”). Patients completed 5.36 skills coach entries per session (standard deviation = 1.95) and took an average of 3.14 min (standard deviation = 0.98 min) to complete the entries. 		
Praveen et al., 2014	SMARTHealth India	Clinical decision support (cardiac)	<ul style="list-style-type: none"> Accessibility: Potential strategies include engaging another intermediary work force (nurse, pharmacists) in the PHC other than the doctor, changes to the working arrangements of the doctors, and bringing the doctor to the village rather than the village to the doctor via structured community visits. Usability: Patients and providers received the technical aspects of the tablet and the CDSS positively. 	<ul style="list-style-type: none"> Adherence: Based on COM-B theory of behavior change, (1) the intervention strategy had potential to transform prevailing health care models, (2) task-shifting of CVD screening to the ASHA was the central driver of change, and (3) despite high acceptability, actual transformation was substantially limited by system-level barriers such as access to doctors and medicines. 	-
Rabbi et al., 2015	MyBehavior	Diet tracking, physical activity tracking	<ul style="list-style-type: none"> Usage: Almost 2.1 million recorded physical activity instances, amounting to more than 8000 hours of physical activity. During the same period, participants labeled 	-	<ul style="list-style-type: none"> Behavior: In the suggestion-rating survey, the experimental group (mean 3.4, SD 1.2, q25=2.75, q50=3, q75=4), with MyBehavior suggestions, intended to follow personalized suggestions more than the

			nearly 850 images of food with annotations. • Data Quality: Users reported MyBehavior activity suggestions to be more actionable.		control group (mean 2.5, SD 1.6, q25=1, q50=2, q75=4) intended to follow the generic suggestions (sig). For walking, 78% (7/9) of participants in the experimental group showed positive trends, whereas 75% (6/8) of participants in the control group exhibited negative trends (sig). For caloric intake, 78% (7/9) of participants in the experimental group showed positive trends, and 57% (4/7) of participants in the control group showed negative trends (nonsig).
Reger et al., 2015	PE Coach	PTSD patient-provider communication	-	-	• Efficiency: Higher levels of satisfaction were reported during prolonged exposure treatment with app than without.
Rubin et al., 2015	Mayo Clinic Acute Stroke Evaluation App	Stroke evaluation checklist	-	-	• Efficiency: All 16 (100%) residents had increased satisfaction with their ability to perform an acute stroke evaluation postintervention but only 9 (56%) of 16 felt the app was more help than hindrance. Staff neurologists conveyed increased satisfaction with resident presentations and decision making when

					compared to preintervention surveys. Stroke clinical data specialists estimated a 50% decrease in data abstraction when the app data were used in the clinical note.
Saeb et al., 2015	Purple Robot	Data collection for depression	<ul style="list-style-type: none"> Accessibility: There were problems in the connection between the early version of Purple Robot and the data server, patients not charging their phones, and unavailability of any network connections for a long period of time for certain locations. 	-	<ul style="list-style-type: none"> Efficiency: Using the normalized entropy feature and a classifier that distinguished participants with depressive symptoms (PHQ-9 score ≥ 5) from those without (PHQ-9 score < 5), there was an accuracy of 86.5%. A regression model that used the same feature to estimate the participants' PHQ-9 scores had an average error of 23.5%.
Scheib et al., 2015	OnTrack Diabetes; Glukose Monitor	Diabetic self-management	<ul style="list-style-type: none"> Usability: 26 (90%) participants felt that neither functionality nor usability of the apps were intuitive or easy to grasp. They reported nonintuitive understanding of the functionality of the apps (26/29, 90%), nonintuitive understanding of the menu navigation/labeling (19/29, 66%), font sizes and representations that were too small (14/29, 48%), and difficulties in recognizing and 	<ul style="list-style-type: none"> Adoption: TAM perceived ease of use: the app test showed that disregarding those usability requirements will result in the greatest impediment when (first) using the apps. The surveyed participants did not intuitively grasp the concept of how to execute the first steps (during first use). The lack of additional benefits is a considerable impact factor, which was revealed during the 	-

			<p>pressing touch-sensitive areas (14/29, 48%), as reasons. They felt apps lacked individually important functions (11/29, 38%), or felt the functions that were offered were unnecessary for their own therapy needs (10/29, 34%). The most important contents of a helpful diabetes app were reported as the ability to add remarks to measured values (9/28, 32%), the definition of thresholds for blood glucose values and highlighting deviating values (7/28, 25%), and a reminder feature for measurement/medication (7/28, 25%)</p>	<p>use of smartphones and tablets, as well as apps.</p>
Schneider et al., 2015	Asthma MD; Asthma Pulse	Asthma self-management	<ul style="list-style-type: none"> • Usability: Participants described the app interfaces as “boring,” “too serious,” and “unappealing.” According to youth, the colors, graphics, and font sizes and types used in the apps were unsatisfactory. To improve app interfaces, participants described “fun” graphics, bold colors, and “bubbly” or “cool” fonts. Participants emphasized tailoring app interfaces for teen 	-

preferences to increase the chances of routine use.

- Data Quality: Desired message content included reminders to measure peak flow, refill prescriptions, make doctors' appointments, and take particular medications at appropriate times. Participants also expressed interest in receiving automatic alerts from the system in response to their self-entered asthma data. Teens desired motivational and supportive messages that encouraged specific asthma management behaviors.

Schreier et al., 2012	app from Health Dialogue (Gesundheitsdialog) project	Diabetic data collection	-	-	<ul style="list-style-type: none"> • Behavior: Of the 403 patients, there were 291 in the App group and 112 in the Web group, categorized by the proportion of data they had transmitted using each method. There was a steady decline of the compliance rate for both groups, at a similar rate during the first year, with a more rapid decline of the compliance rate thereafter for the Web group, which resulted in a significantly higher rate for the App group
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Semple et al., 2015	(developed by QoC Health)	Postoperative recovery monitoring	<ul style="list-style-type: none"> Usage: The mean number of logins was 23.9 (range 7-30) for the breast patients and 19.3 (range 5-30) for the orthopedic patients. The mean number of logins was higher in the first 14 days compared to the 15-30 days post-op for both breast patients (13.4 vs 10.5; $P<.001$) and for the orthopedic patients (13.4 vs 6.0; $P<.001$). Over the 30-day period, 2087 photos were uploaded by the breast patients and 1201 by the orthopedic patients. The mean number of photos uploaded by breast patients was 63 photos (range 11-181) each over the 30-day period, and for orthopedic patients was 38 photos (range 13-160) ($P=.003$). 82% (range 33%-100%) of the breast patients uploaded at least one photo per day, and 58% (range 30%-100%) of the orthopedic patients uploaded at least one photo per day ($P<.001$). 	-	<p>over the whole observation period ($P=0.03$).</p> <ul style="list-style-type: none"> Efficiency: There were no patients who presented clinically with complications that were not identified through monitoring of the mobile phones.
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Shah et al., 2014	SMART	Sickle cell disease monitoring and self-management	<ul style="list-style-type: none"> Usability: Users reported app was easy to use (scale of 0 to 10; median 10, range 5–10), useful to track pain (median 10, range 5–10), and useful to help communicate with providers (median 9, range 8–10). 	-	-
Silveira et al., 2013	Active Lifestyle	Exercise training	-	<ul style="list-style-type: none"> Adherence: App was based on Transtheoretical Model. The most effective motivating strategies for the social group were conditioning through positive social inclusion and external monitoring (all 83%). The social group felt motivated through the awareness of the benefits of physically activity (82%), emotional support (75%), the monitoring of their progress toward the plan (goal setting and self-monitoring) (67%), participation in the collaboration game (58%), positive and negative reinforcement (conditioning) (50%), and the comparison of their performance with other training participants on the bulletin board (42%). 	<ul style="list-style-type: none"> Behavior: Wilcoxon signed rank tests comparing pretest and posttest behavioral scores in each group revealed a trend—with a large effect size—in the social group ($W=1.79$, $P=.07$, $r=0.52$). Hence, the social group tended to change their behavior toward integration of ActiveLifestyle into their daily routine. No behavioral changes were detected in the control group ($P=.28$) or the individual group ($P=.50$). Health: Participants walked significantly faster in the posttest (1.72 m/s) than in the pretest (1.56 m/s; $F_{1,29}=20.1$, $P<.001$, $\eta^2=0.41$). The main effect of group was significant also ($F_{2,29}=5.3$, $P=.01$, $\eta^2=0.27$). Post hoc tests revealed that the individual

group (1.89 m/s) was significantly faster than the control group (1.45 m/s; $t_{19}=3.94$, $P=.003$, $d=1.31$), and faster than the social group (1.58 m/s; $t_{20}=2.05$, $P=.08$, $d=.89$), though not statistically significant.

Simons, Foerster, et al., 2015	Health-Quiz	Physical activity quiz	<ul style="list-style-type: none"> Usage: Relatively high utilization rates of the health quiz were observed. Usability: Mobile health quiz provides added value (usefulness, fun, positive triggers) with low barriers (ease of use, limited time burdens). 	<ul style="list-style-type: none"> Adherence: Based on health behavior change (HAPA and i-change models), long term health behaviours appear to benefit from a grounding in health competences (health perceptions, everyday choices, coping and goal achievement, growth, health identity and self-evaluation). 	<ul style="list-style-type: none"> Behavior: Health behaviours not only improved at 1 and 3 months, but also 10 months after the start.
Simons, Hampe, et al., 2013	Calorie Teller	Diet tracking	<ul style="list-style-type: none"> Usage: Three users used the mApp daily (14 times), the others used it three times or less. Only one expected to continue using the mApp. Usability: Useful (many food items in the database, remembering previous entries, providing instant feedback on nutrients, bar code scanning, enabling mobile logging when on the move) and ease of use and attractiveness were also on average appreciated. 	<ul style="list-style-type: none"> Adherence: Based on health behavior change (HAPA and i-change) models, the app mostly contributed to awareness (three users said to have become more aware) and intention (three users reported increased intentions for healthy eating), but less to self-efficacy (only one user agreed that it contributed, three disagreed, two were neutral) or actual health behavior (again one user 	-

Simons, Hampe, et al., 2014	Calorie Teller; Runkeeper; Pranayama	Diet tracking; physical activity tracking; stress reduction	<ul style="list-style-type: none"> • Usage: Three users used CalorieTeller daily (14 times), the others used it three times or less. Only one expected to continue using it. The time burden was significantly less for the other two mApps (Runkeeper and Pranayama), but still only one participant used them every day, and most participants used them only one, two or three times. • Usability: CalorieTeller was useful (many food items in the database, remembering previous entries, providing instant feedback on nutrients, bar code scanning, enabling mobile logging when on the move) and ease of use and attractiveness were also on average appreciated. 	<p>agreed, three disagreed, two were neutral).</p> <ul style="list-style-type: none"> • Adherence: The ‘maintenance phase’ from HAPA and i-change models is a starting point of a healthier lifestyle which participants endeavour to learn and develop. With every skill and achievement that is added, self-efficacy, motivation and perceived quality of life grows. This further motivates users to pick up other health behaviors too. The apps mostly contributed to awareness (half of the users said to have become more aware) and intention (three users for healthy eating and physical activity, one for stress reduction), but less to self-efficacy (only one user agreed that it contributed for food, zero for the other mApps) or actual health behavior (for each mApp there was one user that agreed, three disagreed, two were neutral). 	-
Tacchini et al., 2015	COGNITIVE - TRAcK	Cognitive impairment	<ul style="list-style-type: none"> • Usage: Users performed the minimum of 32 sessions, with a mean adherence of 84% (33.4/40). 	-	-

		Intervention	<ul style="list-style-type: none"> • Data Quality: 12 participants (75%, 12/16) found the exercises interesting (Q3), and 13 (81%, 13/16) also found the exercises useful for their clinical condition. 		
Torbjornsen et al., 2014	FTA diary	Diabetic self-management	-	-	<ul style="list-style-type: none"> • Behavior: Indication of improvement in the ability of patients to communicate health needs to their health care providers. FTA group reported higher scores for skill and technique acquisition at relieving symptoms compared to the control group (P=.02). • Health: No significant changes between groups for the primary outcome measure HbA1c, although there were declines in the control group and in the intervention groups from baseline to 4-month follow-up.
Tsui et al., 2014	SightBook	Diabetic self-management	-	-	<ul style="list-style-type: none"> • Efficiency: Visual acuity did not consistently correlate with the degree of diabetic retinopathy or macular edema, showing that patients with 20/40 or better visual acuity may have diabetic retinopathy that warrants ophthalmologic treatment.

Turner - McGrievy et al., 2013	Fat Secret's Calorie Counter, My Fitness Pal, Lose it	Diet tracking, physical activity tracking	-	-	<ul style="list-style-type: none"> • Behavior: Physical activity (PA) app users self-monitored exercise more frequently over the 6-month study (2.6 ± 0.5 days/week) and reported greater intentional PA (196.4 ± 45.9 kcal/day) than non-app users (1.2 ± 0.5 days/week PA self-monitoring, $p < 0.01$; 100.9 ± 45.1 kcal/day intentional PA, $p = 0.02$). • Health: PA app users also had a significantly lower BMI at 6 months (31.5 ± 0.5 kg/m²) than non-users (32.5 ± 0.5 kg/m²; $p = 0.02$). PA app users lost more weight ($-3.7 \pm 1.5\%$) than non-app users ($-0.5 \pm 1.5\%$) at 6 months ($p = 0.01$). Change in PA (adjusting for race, age, gender, and randomized group) was significantly related to percent weight loss at 6 months ($F(6,95) = 19.32$; $p < 0.001$). BMI did not differ among the three diet monitoring methods ($p = 0.20$).
Underwood & Kay, 2015	Brush DJ	Motivation for oral health	-	<ul style="list-style-type: none"> • Adherence: Motivation, education, compliance and perceived benefits were four broad themes relating 	<ul style="list-style-type: none"> • Behavior: Eighty-eight percent ($n = 133$) reported the app motivated them to brush their teeth for longer and 92.3% ($n = 144$) would recommend the

to attitudes towards and responses to use of the app.

Brush DJ app to their friends and family.

- Health: Seventy percent (n = 113) reported that their teeth felt cleaner since using the app and 39.3% (n = 57) reported their gums bleed less, with 39.3% (n = 57) reporting no change in bleeding.
- Behavior: Compared to the control group, the intervention group showed a significant improvement on snacking behavior ($\beta = -0.81$, $P < 0.001$).
- Health: Compared to the control group, the intervention group showed a significant improvement on fatigue ($\beta = -3.76$, $P < 0.001$), sleep quality ($\beta = -0.59$, $P = 0.007$), strenuous physical activity ($\beta = 0.17$, $P = 0.028$).

van Drongelen et al., 2014	MORE Energy	Fatigue intervention	<ul style="list-style-type: none"> • Usage: Most of the intervention group participants used the app but never logged on to the website (170 out of 251, 67.7%), while 27 (10.8%) participants used both the app and the website. During the intervention period, 68 (27%) intervention group participants consulted advice during one week only, 54 (22%) consulted advice during two weeks, and 32 (13%) consulted advice during three weeks. A total of 43 (17%) participants consulted the app advice during four weeks or more. 	-	
Vriend et al., 2015	Versterk je Enkel	Ankle sprain prevention	<ul style="list-style-type: none"> • Usage: 8% (n=31 of 82) did not actively use the app, whereas 33% (n=27 of 82) used the App frequently (i.e., multiple times per week). Despite widespread marketing 	-	-

			of the app through a variety of channels, reach and adoption of the App within the target population was found to be low.		
Wiederhold et al., 2014	Positive Technology	Relaxation training tool for stress management	<ul style="list-style-type: none"> • Accessibility: Main advantage for users was the availability and accessibility afforded by a mobile solution. • Usability: It was easy to use and straightforward. 	-	<ul style="list-style-type: none"> • Health: Sixty-eight percent of participants had a reduction in heart rate, indicating physiological relaxation and stabilization after only a few minutes of use and instruction.
Yang et al., 2015	emocha	Data collection among African American men who have sex with men	<ul style="list-style-type: none"> • Usage: A total of 1308 random prompts were sent to participants' mobile phones over follow-up and 968 were completed. This represents an overall compliance rate of 74%, translating to an average of 2.22 random-prompt responses per day per person. 	-	-
Yu et al., 2015	MyMedis and SkinCare (iMHere apps)	Self-care and patient-clinician communication for chronic diseases	<ul style="list-style-type: none"> • Usability: "Ease of use & learnability," "interface quality" and "reliability" received scores lower than 6. Users with a higher degree of dexterity impairment demonstrated more problems in task completion. Users expressed the desire to have simpler apps. 	-	-

Zeng et al., 2015	SmartQuit	Smoking intervention	<ul style="list-style-type: none"> Usage: Lower education (risk ratio [RR] = 0.492; $p = 0.021$), heavier smoking (RR = 0.613; $p=0.033$), and depression (RR=0.958; $p=0.017$) prospectively predicted lower app utilization. 	-	-
Zmily et al., 2014	Adcope	Alzheimer's disease Intervention	<ul style="list-style-type: none"> Usability: The average elapsed time per question between the text-based task (14.04 seconds) and the graphic-based task (12.89 seconds) was significantly different ($P=.047$). There was also a significant difference ($P<.001$) between the average correct answer score between the text-based task (7.60/10) and the graphic-based task (8.30/10), and between the text-based task (31.50/100) and the graphic-based task (27.20/100; $P<.001$). Correlation analysis for the graphic-based task showed that the average elapsed time per question and the workload score were negatively correlated ($-.93$, and $-.79$, respectively) to the participants' performance ($P<.001$ and $P=.006$, respectively). 	-	-