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Health Apps and Behavior Change: Evaluating Effectiveness

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ABSTRACT

The rapid adoption of mobile health (mHealth) applications has transformed the landscape of public health by offering scalable interventions aimed at modifying individual health behaviors. This paper evaluates the effectiveness of health apps in promoting behavior change by examining theoretical frameworks, quantitative and qualitative evaluation methodologies, and key findings from existing research. Evidence highlights mixed results, revealing both successes in improving health outcomes and significant barriers, such as low user retention and limited accessibility. Insights from behavioral science and health psychology underscore the importance of tailoring app features to individual preferences and contexts. Recommendations are made for developers, researchers, and policymakers to foster more inclusive, evidence-based, and sustainable mHealth solutions.

Keywords: Health apps, mHealth, behavior change, digital health, self-care, public health interventions.

INTRODUCTION

Improving patient self-care is a facet of public health digital technology. Devices that gather data on physiological characteristics and the functioning of organ systems, along with the software needed to process, interpret, and display this data to patients in ways that promote the self-care behaviors that can modify or manage specific determinants of health, can be packaged to be sold to health care providers and patients. The second is participatory disease surveillance. Closely connected to digital disease monitoring is the use of the same reported symptoms and results as a way of tracking the disease in essentially, if not necessarily, real-time [1, 2]. Mobile health – or mHealth – applications have exploded in popularity in recent years. There is a growing interest, particularly among researchers and developers, in the potential for app technologies to help modify individual health behaviors. It is estimated that ownership of smartphones increased, and the number of mobile app downloads worldwide was predicted to have climbed to nearly 270 billion. It follows that these technologies are an increasingly attractive channel through which interventions can be delivered on a large scale. There is evidence to suggest that health apps are having an impact on health, with around nine out of ten adults using health apps reportedly achieving improved health outcomes as a result. However, the true potential of health apps has been subject to much debate within the scientific community. To truly understand the relationship between health apps and behavior change, we must first understand how effective they are [3, 4].

Theoretical Frameworks in Behavior Change and Health Apps

In ICT, a user's health behavior needs to be influenced by a variety of user psychological processes. Numerous models and theories are originating in health psychology that explain how a single component of the health application may be employed to stimulate this psychological process. From a cognitive psychology perspective, most of the psychological processes that underpin the behavior change process fall within the umbrella of motivating the user. The motivation to engage in health behavior seems to be derived from the solution to the two questions about the behavior change opportunity: (i) Can I engage in this health behavior? (ii) Do I want to engage in this health behavior? It is from these two questions that users derive efficacy expectations and outcome expectations. These, in turn, bridge the gap between the user's health behavior needs and how the behavior change opportunity is presented to the user via the health application and form the basis of the psychological process needed to effect behavior change in the user [5, 6]. Several health psychology models give a detailed breakdown of motivational processes and how these can be influenced by an intervention. Designing apps with an understanding of these psychological processes could address concerns that many health apps may not have lasting effects because they are unaware of the underlying condition and, indeed, could even undermine it. Using the theories discussed in this paper, app developers can design interventions tailored to the stage of change and the presentation of the behavior to change as perceived by particular users. These decisions can be guided by information gathering about the end users, including the use of technology [7, 8].

Methods for Evaluating Effectiveness

To date, much of the research on health apps relies on either using them as a tool for data collection or considering their development and implementation as technologies that "nudge" users into certain forms of behavior based on their interactions with these tools. Foreground data collection and analytics attempt to more systematically measure and understand a given app's relationship to change against other common technologies for change, while user engagement shapes how the tool functions to appeal to a given user group. However, few tools have been developed specifically for evaluating apps in terms of their effectiveness in supporting particular forms of behavioral change [9, 10]. Two main methodological approaches may be used to develop evaluations investigating these questions: quantitatively via statistical analysis and more qualitative methods. Quantitative methods tend to produce usable evidence for policymakers interested in knowing what works generally and provide other critical stakeholders with strong, utilizable evidence for developing and implementing apps. In contrast, qualitative approaches are best positioned to produce a more nuanced understanding of the mechanisms via which different apps may foster changes, treating health apps in particular as their subjects. Both types of data are needed to ensure a more holistic understanding of the effectiveness of these tools in changing health behavior and practice [11, 12].

Quantitative Approaches

Evaluating the effectiveness of health apps empirically is one way of ascertaining the conditions under which they lead to behavior change. Doing so requires identifying metrics and indicators that serve as theoretical constructs for the efficacy of the intervention – in this case, using the app. For example, in the case of adherence, are there thresholds that better correlate with a health outcome? The trial design most often used to establish the efficacy of an intervention is the randomized controlled trial. RCTs can be adapted to use designs to seek other evidence for what would have happened – without treatment, in alternate treatments, or for individuals – counterfactual analysis. Longitudinal studies, cases that follow a participant's behavior or health over time, are utilized to show the consequence, or what follows the intervention. Several other traits are common among these methods: statistical tests that can be employed to understand the probability that the findings were due to random variation, adjustments for person or group characteristics, and consideration of biases that affect the analyses. Still, given the theoretical basis for the conclusions and the variability across trials, results can be tailored to answer questions about the effectiveness of mHealth interventions [13, 14]. The first step to creating evidence of the effectiveness of health apps is to conduct quantitative evaluations of health app interventions. In using quantitative approaches, researchers assume that measured data are reliable and devoid of any error or random variation. When measuring how a participant has changed, the conclusions rest on observed differences being larger than changes that may have arisen by chance. Objectivity – being aware of the differences in conclusions when people examine the same data – is a component essential for quantitative evaluations where replication and an absence of bias are valued. In the broader sense, numbers can give theoretical constructs a form of reliability, as the numbers, when sound, are estimated through algorithms or steps with minimal subjective intervention. This aspect of evaluation still requires a degree of subjectivity and evaluation to test the internal and external validity of metrics, but consideration of the numerical reductions of theoretical constructs can aid in developing sound evaluation conclusions [15, 16].

Qualitative Approaches

Evaluation methods that fall outside the territory of conventional group-level survey-based designs might be termed 'non-numerical'; although, as we shall see shortly, they are not without their own form of quantification. Focus groups utilize teams of investigators to question groups of participants about their opinions or activities. The results from focus groups can also be used to gain feedback on health apps or their use, but in a group setting, hence the procedure is not substantially different from that of the interview. A focus group is considered a qualitative research technique; no objective measure is obtained, so therefore, the technique is not used to measure the extent to which the feedback is representative of the larger population. Apart from purely being designed to capture open, free-form responses from participants, the focus group can be used as an evaluative tool. This approach is focused in its approach to the use of the interview for the same reasons that maintain the barriers that exist in the context of the development and use of health apps. The degree of satisfaction that a development team can gain from its creation will depend on how it is utilized, the amount of actual engagement the app has with users, and the contexts in which it will be used, i.e., in the real world, where it will be expected to cause behavior change in the long term [17, 18]. Foregrounding the significance of the qualitative input from users of m-health apps was a priority. Particularly in the context of health applications, it is important to understand why users decide not to use a solution or abandon it, as the barriers to utilization will directly affect its effectiveness. A primary tool for capturing such data comes in the form of the participant interview. Semi-structured formats allow for the collection of both quantitative and qualitative anticipations, experiences, or reflections of the individual user. The first of our qualifying criteria was whether or not the research participant undertook to utilize a mobile health application. Some interviewees opted to use m-health capacities on handheld devices, but many did not specify the device. In this sense, part of the aim of my research methodology is to integrate discussions about the use of mobile phones and stand-alone portable devices into the discussion about health apps. Handling the separate inputs of focus group participants and placing their discussions into thematic groups provides a richer and deeper picture of the issues facing potential users of a health app. Most studies agree that qualitative data provide contextual information concerning people's experiences with health app use in addition to the collection of survey data on usability, user experience, and behavior change. In particular, in terms of the application's potential for behavior change, qualitative data are more informative and are valuable concerning an understanding of barriers to app use, and are essential in terms of developing the strategic application of an intervention. Feedback from users to researchers should cause a real change or modification to the design, content, or technical features of the application. If an application is to be embedded in any intervention, the feedback should change the proposed intervention. When software developers work with researchers, there is an expectation among them that feedback should enhance future software builds permanently. It follows that technology design and usability research need to continue long after the initial phases of understanding the end user have been addressed [19, 20].

Key Findings from Existing Research

Existing research: how well do health apps perform? As the health app market continues to expand and investors' confidence in the power of health apps grows, numerous research studies have been conducted to determine just how effective digital health interventions are in changing users' health behavior. Results have been mixed. On the one hand, some studies have found a direct link between using a health app and improved health behavior or health outcomes. Highlighting the importance of content, a recent study found that apps that contain behaviorally designed websites lead to sustained behavior change in 14 of 18 typical health progress fields. Other researchers argued for the importance of user engagement and found that personalized, data-driven feedback in response to tracking can motivate people to lose weight and change their overall lifestyle. Still, other researchers have found small but significant differences in outcomes. They found, for example, that engaging with a smartphone application optimized for health-related goals increased physical activity by approximately 300 steps per day among participants searching for physical activity on discussion boards. Compared with the control group, the active intervention group that downloaded the smartphone application engaged in six more days of physical activity over the six-month study. On the other hand, many studies have found no direct effect of a health app on improving user health. The same team that previously argued in favor of personalized, feedback-based apps reversed course and published more recent research findings that argue that there is, in fact, no clear evidence of effect, and that, to find it, research studies need to be better designed to make higher-quality causal inferences about the effect of using health apps, and to be less biased. Further, results from several of their studies suggest that between 69 and 97% of people who download health and wellness apps stop using them because they find them hard to use, as well as inconvenient, overly time-consuming, or even aesthetically unpleasing, or, for some, unpleasant. Many users also talked about what they see as the dangerous potential of health apps to encourage negative, unhealthy behavior. Notably, we found that a study of a weight loss app showed that a higher level of user engagement in tracking activity, food intake, and weight didn't benefit the user in terms of increased weight loss, even though those who were losing weight were more engaged in the app. Findings such as these firmly suggest that individual differences as well as app features contribute to whether and why people eventually engage in "sticky" usage. Few researchers, however, have tested the degree to which different app features correlate or do not correlate with user activation. Many of the studies provided with the earliest health apps were pilot studies, and "proof of concept" evaluations conducted in small samples. As a result, we cannot generalize findings to larger populations. Still, takeaways may be for hacking health from these studies. In twenty years of research, we have seen that users believe in the likelihood that health apps could be effective, primarily due to the underlying potential of self-tracking, and that they want to use health apps to improve their health [21, 22].

Implications for Future Research and Practice

The field of health apps is changing rapidly. Both health apps and our understanding of what constitutes effective behavior change are continuously evolving. For health apps to remain effective as public health interventions, they should undergo ongoing evaluation and updates. This applies to both standalone apps and apps recommended by healthcare professionals. Moving forward, we make several recommendations for both future research and practice [23, 8]. Technology developers and researchers ought to work more closely with experts from fields such as health psychology, and behavioral science, and people with lived experiences of managing health conditions. This approach would ensure that app features are not just theoretically based but considered through the lens of individual preferences and interactions. Technically, to implement an effective health app as a public health intervention, we should also consider widening the content and coverage to make sure that they appeal to and benefit the largest proportion of the population possible. Additionally, health literacy, including how apps use language, as well as accessibility, should ensure apps have been developed and tested across socio-economic, age, sex, and vulnerable group characteristics to be fully inclusive to all. Furthermore, the use of behavior change techniques and theoretical content can decrease or have no impact on use, as some populations who might benefit from this intervention method don't typically prefer apps to support the management of their health [24, 25].

CONCLUSION

Health apps represent a promising tool for promoting behavior change and enhancing public health outcomes. However, their effectiveness is contingent upon rigorous design, evaluation, and implementation. Integrating principles from health psychology and behavioral science, alongside qualitative user feedback, can enhance app design and functionality, making interventions more personalized and impactful. Future research must address the gaps in methodological rigor and focus on inclusivity, ensuring these tools serve diverse populations. By fostering collaboration among developers, researchers, and healthcare professionals, health apps can achieve their full potential as transformative public health interventions.

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