Proposing a mobile apps acceptance model for users in the health area: A systematic literature review and meta-analysis

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Abstract
Due to rapid advancements in the field of information and communication technologies, mobile health (mHealth) has become a significant topic in the delivery of healthcare. Despite the perceived advantages and the large number of mHealth initiatives, the success of mHealth ultimately relies on whether these initiatives are used; their benefits will be diminished should people not use them. Previous literature has found that the adoption of mHealth by users is not yet widespread, and little research has been conducted on this problem. Therefore, this study identifies the antecedents of the intention to use mHealth and proposes a general model that might prove beneficial in explaining the acceptance of mHealth. The authors performed a quantitative meta-analysis of 49 journal papers published over the past 10 years and systematically reviewed the evidence regarding the most commonly identified factors that may affect the acceptance of mHealth. The findings indicate that the proposed model includes the seven most commonly used relationships in the selected articles. More specifically, the model assumes that perceived usefulness positively affects perceived ease of use and user behavioral intention to use mHealth is commonly influenced by five factors: perceived usefulness, perceived ease of use, attitude toward behavior, subjective norms, and facilitating conditions. The results of this work provide important insights into the predictors of mHealth acceptance for future researchers and practitioners.

Keywords
behavioral intention, mHealth, mobile health, technology acceptance, technology adoption

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Introduction

Due to revolutionary advancements in the field of information and communication technology, the healthcare industry has access to innovations with which to address patients' needs, such as mobile health. Technical advances in terms of mobile phones have created opportunities for healthcare services. Mobile health (mHealth) is one of the most important technologies impacting the healthcare industry. Mobile health refers to the use of mobile phones for providing health services and information, which makes healthcare services more accessible and affordable. Mobile health can increase the control of users by reducing limitations regarding time and location, particularly for those in rural areas. Furthermore, the popularity of mobile phones and their communication features have contributed to user-centered healthcare services and increased the degree of interaction between patients and doctors at a relatively low cost. This innovation has changed the traditional method of providing healthcare services, as online services can be accessed from any place and at any time. Users of mHealth have mentioned several advantages, such as it being simple, accurate, free of charge, convenient, easy to access and reliable.

Despite the potential advantages of mHealth, the success thereof ultimately relies on whether people use such initiatives; their benefits will be diminished should people not use them. Furthermore, the wide adoption of mHealth does not necessarily reflect user uptake of such innovations. For example, a study found that although the majority of citizens surveyed displayed a positive attitude toward mHealth, only a few participants had actually used it. Similarly, a study conducted in Bangladesh reported that, although people were aware of mHealth, only 5% of citizens (based on 4915 responses) had used such initiatives. This finding might be attributed to users usually being more reluctant to use health-related innovations than other innovative products. The aforementioned literature highlights the potential of mHealth and provides evidence of the existence of issues that hinder its use. These aspects are important not just because these services represent a significant investment but also because intended users will not experience the potential advantages of using them. While little research has been conducted on understanding this new phenomenon, it is essential to investigate factors that support the effective utilization of mHealth.

In this regard, researchers have been investigating user acceptance of mHealth and extending technology acceptance theories with various factors for more than a decade, including the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), and the UTAUT2. Previous research has led to a large number of investigated variables and proposed technology acceptance theories. To address this problem, it is necessary to propose a general model for the acceptance of mHealth that is applicable to all types of mHealth services, systems, and applications. Therefore, the objectives of this paper are to (1) systematically review related articles within the domain of mHealth acceptance, (2) identify the most commonly investigated significant relationships in these articles, (3) assess the strength of the identified relationships, and (4) propose a general model with latent constructs to understand the acceptance of mHealth.

This paper is organized as follows. First, literature related to the acceptance of mHealth is reviewed. The research methodology is outlined in Section 3. Thereafter, Section 5 contains the research findings and discussion. Finally, the implications, limitations, and conclusion are presented in Sections 5, 6, and 7, respectively.

Literature review

Researchers have used several technology acceptance theories and models (such as the TAM, the UTAT, and the UTAUT2) to explain user acceptance and the use of new innovations. One of the
most influential models, the TAM, was introduced by Davis in 1986; this model was developed based on the theory of reasoned action (TRA).\textsuperscript{19} According to Google Scholar, the TAM has been cited more than 54,000 times (as of September 23, 2020).\textsuperscript{20} The TAM proposes that two main constructs (perceived ease of use (PEOU) and perceived usefulness (PU)) determine user attitudes toward a particular innovation. The TAM posits that the primary antecedent of user behavior is intention, which is the agent of user acceptance.\textsuperscript{21} The two main constructs can be impacted by external factors related to the innovation under investigation. However, the TAM has been criticized by researchers for its low explanatory power\textsuperscript{22–24} and lack of moderating variables.\textsuperscript{25,26} This criticism might justify the emergence of the UTAUT, which was developed based on the examination of eight technology acceptance theories and models: the TRA, the theory of planned behavior (TPB), the TAM, the motivation model, the augmented TAM, the model of PC utilization (MCPU), the innovation diffusion theory (IDT), and social cognitive theory (SCT).\textsuperscript{26} The UTAUT posits that user intention and actual behavior (AB) are determined by four independent factors, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, as well as four moderating variables, namely gender, age, experience, and voluntariness of use. The UTAUT was recently further extended to explain consumer behavior.\textsuperscript{27} The developed model, the UTAUT2, added three more independent variables, namely hedonic motivation, price value, and habit, and three moderating variables, namely age, gender, and experience. However, both the UTAUT and the UTAUT2 have been criticized for result bias across cultures (e.g. El-Masri and Tarhini\textsuperscript{28}). It is evident from this brief review that each model has its own limitations; therefore, proposing a general model is, perhaps, an appropriate solution to overcome these limitations.

Despite the abundance of user acceptance studies in the domain of information systems, literature related to mHealth acceptance is scarce.\textsuperscript{5,18} Moreover, the existing literature is associated with several limitations. First, most of these studies only adopted technical factors (such as mobile anxiety, performance expectancy, and effort expectancy) from the aforementioned technology acceptance models (e.g. Dwivedi et al.\textsuperscript{1}; Hoque and Sorwar\textsuperscript{5}; Cho\textsuperscript{15}; Sezgin et al.\textsuperscript{29}). However, the acceptance of mHealth is also considered a health-related behavior, which necessitates the investigation of health-related factors. Second, although the majority of these studies used traditional technology acceptance models such as the TAM, the UTAUT, and the UTAUT2, they produced inconsistent results. For example, it has been empirically demonstrated that the relationship between effort expectancy and user intention is significant.\textsuperscript{1,5} However, the results of a study conducted in Turkey found an insignificant effect.\textsuperscript{29} The underlying reason for these contradicting results can be attributed to differences in study contexts, cultures, samples, and statistical techniques. These inconsistent findings can cause confusion among researchers and hinder the acceptance of mHealth. Finally, the number of quantitative research studies that have been conducted to obtain a comprehensive understanding of the relationships between the proposed variables and the behavioral intention to use mHealth is severely limited.\textsuperscript{30} This literature review highlights the importance of proposing a general model that can be useful for understanding the acceptance of mHealth.

**Research methodology**

The current study proposes a general model for the acceptance of mHealth based on the most commonly used significant relationships. Therefore, a systematic review and a quantitative meta-analysis were conducted in accordance with previous studies\textsuperscript{2,31,32} to analyze the results of published articles within the domain of mHealth acceptance. To ensure the inclusion of relevant articles, this review targets various types of mHealth (such as services, applications, and mobile medical records) and various user groups (such as elderly people, patients, physicians, and consumers).
This research follows the guidelines provided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement, which includes four phases: identification, screening, eligibility, and inclusion.33

**Article identification**

Following the PRISMA guidelines, a systematic literature search to identify citations was conducted using a variety of well-known online scientific databases, such as ScienceDirect, Web of Science, SpringerLink, Taylor and Francis, Emerald, SAGE, IEEE Xplore, and JMIR Publications. The search terms were selected based on two factors: innovation (mHealth) and technology acceptance theories. The terms were a combination of two groups of keywords (mHealth OR m-health OR mobile health) AND (technology acceptance OR technology adoption OR theory of reasoned action OR theory of planned behavior OR TAM OR UTAUT OR UTAUT2). The authors deliberately used many keywords and broad terms to minimize the possibility that relevant papers would be overlooked. Furthermore, review papers within the domain of mHealth2,12,30,34 were carefully searched to ensure the inclusion of relevant studies. A total of 2402 citations were obtained from this search.

**Article screening**

The second phase of the PRISMA guidelines involves screening the selected articles. Thus, the principal author and co-author carried out a screening stage for the retrieved citations based on each article’s title, abstract, and keywords (if needed). Consequently, 509 citations were removed due to duplication, and 1893 citations were retained.

**Article eligibility**

Following the PRISMA guidelines and to ensure the quality and consistency of the identified articles, several criteria were used for article eligibility. An article was selected if the following applied: (1) It had investigated the acceptance of mHealth. (2) It had been published in a peer-reviewed scientific journal to ensure the quality of articles32,35; thus, conference proceedings, student dissertations and unpublished studies were excluded. (3) It was written in English. (4) It presented quantitative empirical results; therefore, qualitative, and/or theoretical studies were removed.2,12,30 (5) It was published within the past 10 years (i.e. between 2010 and 2020), as mHealth acceptance was not widely adopted before 2010. (6) Finally, it reported the methodology, path coefficients and significance level.2,30,32 Every article was reviewed and selected by the principal author and co-author based on the aforementioned criteria. This stage resulted in 49 eligible papers, which are listed in the Appendix. Figure 1 summarizes the entire article selection process.

Having completed the systematic review of relevant articles, the meta-analysis was subsequently conducted by extracting and analyzing each article’s information.

**Data extraction**

Following previous review studies2,12,30,34 each article’s information was extracted by reading through the text, including article characteristics (article code, title, publication year, journal name, tested system, study design, research country, and sample size), the constructs included in the model (research model, independent variables, dependent variables, and moderating variables), and the statistics (statistical technique, statistical software package, path coefficients, significance
level, and explained variance). The information was stored using Microsoft Office Excel 2019. The models utilized in the eligible papers were inconsistent; researchers used different terms to indicate the same construct, and therefore similar constructs were combined into a single terminology. For instance, PEOU, PU, facilitating conditions (FC), and subjective norm (SN) were integrated with effort expectancy, performance expectancy, perceived behavioral control, and social influence, respectively.2

Following the data extraction stage, the most commonly used significant relationships in the selected articles were identified using the count function in Microsoft Office Excel 2019. One hundred constructs were examined in the selected articles, with 26 dependent variables and 170 relationships. However, only seven relationships were confirmed as the most commonly used significant relationships in the selected articles (see Table 5). The general model for the acceptance of mHealth is proposed based on the average of path coefficients and the significance level of the selected relationships (Figure 2).

Data analysis
Path coefficients were employed to identify the significant relationships among constructs. Path coefficients refer to the strength of relationships between factors and can range from +1 to −1.36 A path coefficient value of +1 indicates a strong positive correlation between factors, whereas −1 indicates a strong negative correlation.37 A path coefficient value of 0 indicates no relationship between the two factors. It has been suggested that path coefficients with 0.1, 0.3, or 0.5 are considered low, moderate, or high effect sizes, respectively.38

Findings and discussion
Study characteristics
As displayed in the Appendix, 49 articles were selected for this study (see Table 1). More than 73% of these articles were written in the past 5 years (see Table 2). The studies were mostly conducted
Figure 2. The proposed conceptual model.

Table 1. Distribution of articles by journal.

| Scientific journal                                                      | Count of articles |
|------------------------------------------------------------------------|-------------------|
| International Journal of Medical Informatics                           | 6                 |
| BMC Medical Informatics and Decision Making                            | 5                 |
| International Journal of Information Management                       | 5                 |
| Electron Markets                                                       | 3                 |
| Electronic Commerce Research and Applications                          | 2                 |
| Informatics for Health and Social Care                                 | 2                 |
| JMIR Mhealth and Uhealth                                              | 2                 |
| Convergence: The International Journal of Research into New Media Technologies | 1                 |
| Frontiers in Psychology                                               | 1                 |
| Government Information Quarterly                                       | 1                 |
| Health Education & Behavior                                           | 1                 |
| Health Informatics Journal                                            | 1                 |
| Health Information Management Journal                                  | 1                 |
| Health Policy and Technology                                           | 1                 |
| Information Development                                                | 1                 |

(Continued)
Table 1. (Continued)

| Scientific journal                                      | Count of articles |
|---------------------------------------------------------|-------------------|
| Information Technology for Development                  | 1                 |
| International Journal of Human–Computer Interaction     | 1                 |
| International Journal of Production Research            | 1                 |
| JMIR Medical Informatics                                | 1                 |
| Journal of American College Health                      | 1                 |
| Journal of Business Research                            | 1                 |
| Journal of Enterprise Information Management             | 1                 |
| Journal of Medical Internet Research                    | 1                 |
| Journal of Medical Systems                              | 1                 |
| Journal of Women & Aging                                | 1                 |
| Online Information Review                               | 1                 |
| Services Marketing Quarterly                            | 1                 |
| Technology in Society                                   | 1                 |
| Telecommunications Policy                               | 1                 |
| Telemedicine and e-Health                               | 1                 |
| The Service Industries Journal                          | 1                 |

Table 2. Distribution of articles by year.

| Year  | Count of articles |
|-------|-------------------|
| 2010  | 1                 |
| 2011  | 1                 |
| 2012  | 2                 |
| 2013  | 4                 |
| 2014  | 2                 |
| 2015  | 3                 |
| 2016  | 7                 |
| 2017  | 8                 |
| 2018  | 9                 |
| 2019  | 10                |
| 2020  | 2                 |

in China and Taiwan (see Table 3). This indicates that China and Taiwan have active developments in the area of mHealth. This can be attributed to the increasing number of elderly people and is associated with the dramatic growth in medical expenses for aging populations. Thus, governments, practitioners and researchers might consider mHealth as an effective solution for the costs of medical care. Among the 100 constructs investigated in the selected articles, behavioral intention (BI), PU, PEOU, SN, FC, and attitude were the most commonly used (see Table 4). Table 5 lists the most commonly used significant relationships among the 170 studied in the selected articles (PU → BI, PEOU → BI, PEOU → PU, SN → BI, FC → BI, BI → AB, and attitude → BI).

Perceived ease of use

Perceived ease of use has been a key determinant in many technology acceptance models, such as the TAM, the TAM2, the TAM3, the augmented TAM, and the determinants of the PEOU model.
### Table 3. Distribution of articles by country.

| Country          | Count of articles |
|------------------|-------------------|
| China            | 15                |
| Taiwan           | 5                 |
| Bangladesh       | 4                 |
| Singapore        | 3                 |
| South Korea      | 3                 |
| USA              | 3                 |
| Canada           | 2                 |
| Portugal         | 2                 |
| Turkey           | 2                 |
| Ethiopia         | 1                 |
| France           | 1                 |
| Germany          | 1                 |
| Ghana            | 1                 |
| Israel           | 1                 |
| Japan            | 1                 |
| Kenya            | 1                 |
| South Africa     | 1                 |
| Sri Lanka        | 1                 |
| UK               | 1                 |

### Table 4. Distribution of most commonly used constructs.

| Construct                                | Count of articles |
|------------------------------------------|-------------------|
| Behavioral intention                     | 37                |
| Perceived usefulness                     | 36                |
| Perceived ease of use                    | 30                |
| Subjective norm                          | 16                |
| Facilitating conditions                   | 12                |
| Attitude                                 | 10                |
| Actual behavior                          | 10                |
| Technical anxiety                         | 9                 |
| Continuous behavioral intention           | 8                 |
| Value                                     | 8                 |
| Satisfaction                              | 7                 |

### Table 5. Distribution of most commonly used significant relationships.

| Relationship                               | Count of articles |
|--------------------------------------------|-------------------|
| Perceived usefulness → behavioral intention| 22                |
| Perceived ease of use → behavioral intention| 12                |
| Perceived ease of use → perceived usefulness| 11                |
| Subjective norm → behavioral intention     | 10                |
| Facilitating conditions → behavioral intention| 7                 |
| Behavioral intention → actual behavior    | 7                 |
| Attitude → behavioral intention           | 5                 |
Other models use different terms for the same construct, such as ease of use in the IDT, and effort expectancy in the UTAUT and the UTAUT2. In accordance with these models, users perceiving mHealth types as easy to use are more likely to use them than those who do not perceive them in this manner, and vice versa. Perceived ease of use can be defined, in this context, as the degree to which users believe that utilizing mHealth types is not a considerable effort. Our review reveals that this factor was examined in 30 articles, indicating that PEOU is the second most commonly used predictor in the domain of mHealth (see Table 4).

The literature provides evidence of the significant effect of PEOU on users’ PU of mHealth. Out of 49 articles selected in this study, the relationship between PEOU and PU was examined in 12 articles, and 11 (92%) of these articles found a significant positive relationship between the two factors (see Table 6). Our results in Table 6 reveal that, across all mHealth types, the average path coefficient value of the 11 articles is 0.40. According to the guidelines suggested in Cohen, the effect of PEOU on PU is medium. Therefore, the relationship between PEOU and PU is included in the general model for the acceptance of mHealth.

Our findings indicate that the effect of PEOU on PU is relatively high compared with the other relationships in the proposed model (see Figure 2). This finding suggests that when users perceive mHealth to be easy to use, they are more likely to perceive it as being useful. Users prefer mHealth types that require little effort to use, which, in turn, enhances their perception toward their usefulness. Such a result is unsurprising, as easy-to-use mHealth types save users time and enable users to utilize them more effectively. This result is in accordance with previously developed models, such as the TAM, the augmented TAM, the determinants of the PEOU model, the TAM2 and the TAM3.

Compared to other behavior-change models in healthcare science, the relationship between PEOU and PU was demonstrated. For example, the acceptance of wearable health technologies was examined using older adults in Hong Kong and Taiwan. The authors confirmed that when older adults perceive a wearable health technology as easy to use, they are more likely to perceive it as being useful. Concerning electronic medical records, research articles have revealed the same result. Furthermore, a meta-analysis of health information technologies using 67 studies revealed that the effect size of PEOU on PU is 0.52, which was deemed high. Therefore, our research is consistent with past studies and found evidence of a positive effect of PEOU on PU.

In contrast, the relationship between PEOU and BI has been demonstrated in various technology acceptance models such as the TAM, the TAM2, the TAM3, the determinants of the PEOU model, the IDT, the UTAUT, and the UTAUT2. Regarding the effect of PEOU on BI to use mHealth, of 49 articles selected in this study, the relationship between PEOU and BI was examined in 19 articles, and 12 (63%) of these found a significant positive relationship between the two factors (see Table 7). This finding indicates that the relationship between PEOU and BI is the second most important relationship in the domain of mHealth. This result implies that, without an obvious PEOU, users’ BI to use mHealth types is reduced, which affects their actual use of mHealth types. One plausible justification for this finding is that mHealth types are relatively new technologies; therefore, PEOU is essential for users’ BI to use them.

The results in Table 7 reveal that, across all mHealth types, the average path coefficient value of the 12 articles is 0.35. According to the guidelines suggested in [39], the effect of PEOU on BI is medium. Therefore, the relationship between PEOU and BI is included in the general model for the acceptance of mHealth (see Figure 2).

Compared to other behavior-change models in health science, the relationship between PEOU and BI was demonstrated in several review studies. Based on a systematic review of 97 studies, it was concluded that the effect of PEOU on the use of personal electronic health records is positively significant. Likewise, a systematic review and meta-analysis of health information technologies
Table 6. Articles examining the effect of PEOU on PU.

| Study            | Technology                          | Theory | Country      | Target group       | Sample size | Significant? | Beta     |
|------------------|-------------------------------------|--------|--------------|--------------------|-------------|--------------|----------|
| Zhang et al.⁴    | Mobile health service               | TAM    | China        | Users              | 650         | Yes          | 0.61***  |
| Cho¹⁵            | Mobile health application           | TAM    | Korea        | Students           | 343         | Yes          | 0.28***  |
| Dou et al.¹⁷     | Mobile health application           | TAM    | China        | Patients           | 157         | Yes          | 0.14*    |
| Tsai et al.¹⁸    | Telehealth                          | TAM, IDT, SQB | Taiwan  | Patients           | 281         | No           |          |
| Xue et al.⁴²     | Mobile health application           | TAM    | Singapore    | Elderly women      | 700         | Yes          | 0.11**   |
| Hung and Jen ⁴³  | Mobile health management system     | TAM    | Taiwan       | Students           | 170         | Yes          | 0.66**   |
| Guo et al.⁴⁴     | Mobile health service               | TAM    | China        | Elderly consumers  | 204         | Yes          | 0.46**   |
| Kuo et al.⁴⁵     | Mobile electronic medical record    | TAM    | Taiwan       | Nurses             | 665         | Yes          | 0.53**   |
| Liu and Cheng⁴⁶  | Mobile electronic medical record    | TAM    | Taiwan       | Physicians         | 158         | Yes          | 0.59***  |
| Miao et al.⁴¹    | Mobile health service               | TAM    | China        | Older and middle-age patients | 519 | Yes          | 0.65***  |
| Beldad and Hegner⁴⁷ | Mobile health application          | TAM    | Germany      | Users              | 476         | Yes          | 0.17***  |
| Zhang et al.⁴⁸   | Mobile health application           | UTAUT  | China        | Patients           | 746         | Yes          | 0.20**   |

Sample size 5,069
Average of path coefficient 0.40

IDT: innovation diffusion theory; SQB: status quo bias; TAM: technology acceptance model.

*p < 0.05. **p < 0.01. ***p < 0.001.
Table 7. Articles examining the effect of PEOU on BI.

| Study                        | Technology                        | Technology Theory | Country       | Target group            | Sample size | Significant? | Beta     |
|------------------------------|-----------------------------------|-------------------|---------------|-------------------------|-------------|--------------|----------|
| Dwivedi et al. 1             | Mobile health service             | UTAUT2            | USA           | Patients                | 1,125       | Yes          | 0.36*    |
|                              |                                   |                   | Canada        |                         |             |              | 0.39*    |
|                              |                                   |                   | Bangladesh    |                         |             |              | 0.38*    |
| Alam et al. 3                | Mobile health application         | UTAUT             | Bangladesh    | Generation Y consumers  | 296         | No           |          |
| Hoque and Sorwar 5           | Mobile health service             | UTAUT             | Bangladesh    | Elderly people          | 300         | Yes          | 0.19*    |
| Sezgin et al. 7              | Mobile health application         | TAM               | Turkey        | Physicians              | 122         | Yes          | 0.22*    |
| Sezgin et al. 29             | Mobile health application         | TAM               | Turkey        | Physicians              | 151         | No           |          |
| Xue et al. 52                | Mobile health application         | TAM               | Singapore     | Elderly women           | 700         | Yes          | 0.23**   |
| Guo et al. 54                | Mobile health service             | TAM               | China         | Elderly consumers       | 204         | Yes          | 0.20*    |
| Kuo et al. 55                | Mobile electronic medical record  | TAM               | Taiwan        | Nurses                  | 665         | Yes          | 0.38***  |
| Liu and Cheng 66             | Mobile electronic medical record  | TAM               | Taiwan        | Physicians              | 158         | Yes          | 0.39***  |
| Miao et al. 41               | Mobile health service             | TAM               | China         | Older and middle-age patients | 519     | Yes          | 0.57***  |
| Zhang et al. 48              | Mobile health application         | UTAUT             | China         | Patients                | 746         | Yes          | 0.11**   |
| Lim et al. 54                | Mobile web application            | TAM               | Singapore     | Students, staff         | 164         | No           |          |
| Hoque 55                     | Mobile health service             | UTAUT             | Bangladesh    | Students                | 227         | Yes          | 0.7*     |
| Nunes et al. 56              | Mobile health application         | UTAUT             | Portugal      | Users                   | 394         | No           |          |
| Zhu et al. 57                | Mobile health management system   | TAM               | China         | Patients                | 279         | Yes          | 0.45**   |
| Lwin et al. 58               | Mobile health application         | NR                | Sri Lanka     | Users                   | 404         | Yes          | 0.27***  |
| Duarte et al. 59             | Mobile health application         | UTAUT2            | Portugal      | Users                   | 120         | No           |          |
| Deng et al. 60               | Mobile health application         | TAM               | China         | Patients                | 388         | No           |          |
| Alam et al. 61               | Mobile health app                 | UTAUT2            | Bangladesh    | Young users             | 400         | No           |          |
| Sample size                  |                                   |                   |               |                         | 7,362       |              |          |

Average of path coefficient: 0.35

NR: not reported; TAM: technology acceptance model; UTAUT: unified theory of acceptance and use of technology; UTAUT2: extended unified theory of acceptance and use of technology.

*p < 0.05. **p < 0.01. ***p < 0.001.
using 67 papers demonstrated that the effect size of PEOU on BI is 0.21.\textsuperscript{12} Another systematic review,\textsuperscript{62} which investigated factors influencing health information technology adoption by seniors, presented the same results. Furthermore, the positive effect of PEOU on BI was also confirmed by reviewing 85 papers on the acceptance of mobile health applications.\textsuperscript{34} In mobile health services, a meta-analysis found that PEOU has a positive impact on BI to use mHealth services.\textsuperscript{30} In contrast, factors affecting the acceptance of electronic health records by physicians in Bangladesh were examined in another study.\textsuperscript{51} The authors revealed that effort expectancy (like PEOU) does not have a significant effect on BI, which was attributed to barriers such as the infrastructure of information and communication technologies, lack of training and computer skills, and slow Internet connections. However, this is not the case in many contexts.

\textbf{Perceived usefulness}

Perceived usefulness is considered a key determinant in many technology acceptance models, such as the TAM, the TAM2, the TAM3, the augmented TAM, and the determinants of PEOU model. Other models use different terms for the same construct, such as job-fit in the MPCU, outcome expectations-performance in SCT, relative advantage in the IDT and performance expectancy in the UTAUT and the UTAUT2. In accordance with these models, users perceiving mHealth types as useful are more likely to use them. In contrast, users perceiving mHealth types as not useful are more likely to avoid them. Perceived usefulness can be defined, for the purpose of this study, as the degree to which users believe that utilizing mHealth types would improve their health.\textsuperscript{19} Our review found that this factor was examined in 36 articles, indicating that PU is the most commonly used predictor in the domain of mHealth types (see Table 4).

Existing studies support our findings that PU is an important contributing factor to users’ BI to utilize mHealth types (e.g. see Table 8). Other technology acceptance models, such as the TAM, the TAM2, the TAM3, the augmented TAM, the determinants of PEOU model, the IDT, the UTAUT, and the UTAUT2, assume that PU is a direct antecedent of users’ BI. Out of 49 articles selected in this study, the relationship between PU and BI was examined in 25 articles, and 23 (92\%) of these found a significant positive relationship between the two factors (see Table 8). This finding indicates that the relationship between PU and BI is the most important relationship in the domain of mHealth. This finding is consistent with past studies in technology acceptance,\textsuperscript{20,21} in which individuals are mainly driven by the usefulness of the investigated technology.

The results in Table 8 reveal that, across all mHealth types, the average path coefficient value of the 23 articles is 0.33. According to the guidelines suggested by Cohen,\textsuperscript{38} the effect of PU on BI is medium. Therefore, the relationship between PU and BI is included in the general model for the acceptance of mHealth (see Figure 2).

Compared to other behavior-change models in health science, certain review studies demonstrated the relationship between PU and BI. Based on a systematic review of 97 studies, it was concluded that the effect of PU on the use of electronic personal health records is positively significant.\textsuperscript{35} Similarly, a systematic review and meta-analysis of health information technologies using 67 articles revealed that the relationship between PU and BI had been examined in 51 articles with an effect size of 0.41,\textsuperscript{12} indicating the importance of PU when examining the adoption of health technologies. Another systematic review,\textsuperscript{62} which investigated factors influencing health information technology adoption by seniors, yielded the same results. Furthermore, the positive effect of PU on BI was also confirmed by reviewing 85 papers on the acceptance of mobile health applications.\textsuperscript{34} In mobile health services, a meta-analysis found that PU has a positive impact on BI to use mHealth services.\textsuperscript{30} Therefore, this research is in accordance with most previous literature
| Study               | Technology                  | Theory        | Country                | Target group                      | Sample size | Significant? | Beta  |
|---------------------|-----------------------------|---------------|------------------------|-----------------------------------|-------------|--------------|-------|
| Dwivedi et al.¹     | Mobile health service       | UTAUT2        | USA                    | Patients                          | 1,125       | Yes          | 0.14* |
|                     |                             |               | Canada                 |                                   |             |              |       |
|                     |                             |               | Bangladesh             |                                   |             |              |       |
| Alam et al.³        | Mobile health application   | UTAUT         | Bangladesh             | Generation Y consumers            | 296         | Yes          | 0.26* |
| Zhang et al.⁴       | Mobile health service       | TAM           | China                  | Users                             | 650         | Yes          | 0.30***|
| Hoque and Sorwar⁵   | Mobile health service       | UTAUT         | Bangladesh             | Elderly people                    | 300         | Yes          | 0.32* |
| Sezgin et al.⁷      | Mobile health application   | TAM           | Turkey                 | Physicians                        | 122         | No           |       |
| Hoossain¹⁶          | Mobile health service       | IS Success    | Bangladesh             | Users                             | 199         | Yes          | 0.72**|
| Dou et al.¹⁷        | Mobile health application   | TAM           | China                  | Patients                          | 157         | Yes          | 0.62**|
| Tsai et al.¹⁸       | Mobile health application   | TAM, IDT, SQB | Taiwan                | Patients                          | 281         | Yes          | 0.21**|
| Sezgin et al.²⁹     | Mobile health application   | TAM           | Turkey                 | Physicians                        | 151         | Yes          | 0.36***|
| Xue et al.³²        | Mobile health application   | TAM           | Singapore              | Elderly women                     | 700         | Yes          | 0.14* |
| Hung and Jen⁴³      | Mobile health management system | TAM       | Taiwan                | Students                          | 170         | Yes          | 0.20* |
| Guo et al.⁴⁴        | Mobile health service       | TAM           | China                  | Elderly consumers                 | 204         | Yes          | 0.42**|
| Kuo et al.⁴⁵        | Mobile electronic medical record | TAM    | Taiwan                | Nurses                            | 665         | Yes          | 0.27***|
| Liu and Cheng⁴⁶     | Mobile electronic medical record | TAM    | Taiwan                | physicians                        | 158         | Yes          | 0.31***|
| Lim et al.⁵⁴        | Mobile web application      | TAM           | Singapore              | Students, staff                    | 164         | Yes          | 0.40***|
| Hoque⁵⁵             | Mobile health service       | UTAUT         | Bangladesh             | Students                          | 227         | Yes          | 0.21* |
| Nunes et al.⁵⁶      | Mobile health application   | UTAUT         | Portugal               | Users                             | 394         | Yes          | 0.79***|
| Zhu et al.⁵⁷        | Mobile health management system | TAM    | China                  | Patients                          | 279         | Yes          | 0.49***|
| Lwin et al.⁵⁸       | Mobile health application   | NR            | Sri Lanka              | Users                             | 404         | No           |       |
| Duarte and Pinho⁵⁹  | Mobile health application   | UTAUT2        | Portugal               | Users                             | 120         | Yes          | 0.45***|
| Deng et al.⁶⁰       | Mobile health application   | TAM           | China                  | Patients                          | 388         | Yes          | 0.13* |
| Alam et al.⁶¹       | Mobile health app           | UTAUT2        | Bangladesh             | Young users                       | 400         | Yes          | 0.09**|
| Cocosila and Archer⁶³ | Mobile health application   | SMS           | Canada                 | Users                             | 50          | Yes          | 0.75***|
| Kissi et al.⁶⁴      | Telehealth                  | TAM           | Ghana                  | Physicians                        | 543         | Yes          | 0.09* |
| Sample size         |                             |               |                        |                                   | 8,147       |              |       |
| Average of path coefficient |                 |               |                        |                                   |             |              | 0.33  |

IDT: innovation diffusion theory; NR: not reported; SQB: status quo bias; TAM: technology acceptance model; UTAUT: unified theory of acceptance and use of technology; UTAUT2: extended unified theory of acceptance and use of technology.

*p < 0.05. **p < 0.01. ***p < 0.001.
concerning health behavior-change models, and the results support the presence of a positive impact of PU on BI.

**Subjective norms**

Subjective norms can be described as a “person’s perception that most people who are important to him think he should or should not perform the behavior in question.”\(^{65}\) In other words, an individual experiences external pressure from important people, and this pressure might affect his or her engagement in a certain behavior.\(^{26}\) Researchers have used different terms to refer to the same construct, such as social influence and social norms. Indicating the significance of SN, this factor has been demonstrated to be a predictor of user behavior in various technology acceptance models such as the TRA, the TPB, the TAM2, the A-TAM, the TAM3, the UTAUT, the UTAUT2, and the MPCU. Since the TAM excludes social influence factors, it has been criticized for failing to appropriately consider social factors.\(^{66}\) Our review demonstrates that SN was examined in 16 articles, indicating that it is the third most commonly used predictor in the domain of mobile health types (see Table 4).

Regarding the effect of SN on users’ BI to use mHealth, the relationship between SN and BI was examined in 16 of the 49 articles selected in this study, and 10 (63%) of these found a significant positive relationship between the two factors (see Table 9). This finding indicates that the relationship between SN and BI is the fourth most important relationship in the domain of mHealth. The results in Table 9 reveal that, across all mHealth types, the average path coefficient value of the 10 articles is 0.31. According to the guidelines suggested in [39], the effect of SN on BI is medium. Therefore, the relationship between SN and BI is included in the general model for the acceptance of mHealth (see Figure 2).

In comparison to health models, review studies provided evidence of the importance of SN in the acceptance of health technologies. A systematic review and meta-analysis of health information technologies using 67 studies disclosed that the relationship between SN and BI had been examined in 18 articles with an effect size of 0.19.\(^{12}\) Another systematic review,\(^{62}\) which investigated factors influencing health information technology adoption by seniors, demonstrated the same results. Furthermore, the positive effect of SN on BI was also confirmed by reviewing 85 papers on the acceptance of mobile health applications.\(^{34}\) In mobile health services, a meta-analysis found that SN had been examined in 25 studies and has a positive impact on BI to use mHealth services.\(^{30}\) Thus, our research is in line with the aforementioned studies and confirms the presence of a strong and positive effect of SN on BI.

**Facilitating conditions**

The term FC refers to the degree to which users believe that organizational and technical infrastructures exist to perform a certain action.\(^{27}\) Alternatively, FC ensures the availability of resources (e.g., time and money) and technical resources (e.g., Internet and mobile devices).\(^{70}\) In the context of mHealth, FC measures whether users have the required resources to use mHealth types. This factor is significant and has been demonstrated to be an antecedent of user behavior in technology acceptance theories, such as TPB, the UTAUT, the UTAUT2, and the MPCU. Researchers in the field of technology acceptance have used different terms to refer to the FC construct, such as perceived behavioral control in the TPB.\(^{26}\)

Existing studies have demonstrated the influence of FC on users’ BI to use mHealth types. Out of 49 articles selected in this study, the relationship between FC and BI was examined in 11, and seven (64%) of these found a significant positive relationship between the two factors (see Table 10).
| Study                  | Technology                      | Theory   | Country     | Target group            | Sample size | Significant? | Beta   |
|-----------------------|---------------------------------|----------|-------------|-------------------------|-------------|--------------|--------|
| Dwivedi et al.¹       | Mobile health service           | UTAUT2   | USA         | Patients                | 1,125       | Yes          | 0.13*  |
|                       |                                 |          | Canada      |                          |             |              | 0.11*  |
|                       |                                 |          | Bangladesh  |                          |             |              | 0.54*  |
| Alam et al.³          | Mobile health application       | UTAUT    | Bangladesh  | Generation Y consumers  | 296         | Yes          | 0.21*  |
| Hoque and Sorwar⁵     | Mobile health service           | UTAUT    | Bangladesh  | Elderly people          | 300         | Yes          | 0.14*  |
| Sezgin et al.⁷        | Mobile health application       | TAM      | Turkey      | Physicians              | 122         | No           |        |
| Sezgin et al.²⁹       | Mobile health application       | TAM      | Turkey      | Physicians              | 151         | No           |        |
| Xue et al.⁴²          | Mobile health application       | TAM      | Singapore   | Elderly women           | 700         | Yes          | 0.25** |
| Zhang et al.⁴⁸        | Mobile health application       | UTAUT    | China       | Patients                | 746         | Yes          | 0.22*  |
| Hoque⁵⁵               | Mobile health service           | UTAUT    | Bangladesh  | Students                | 227         | Yes          | 0.22*  |
| Nunes et al.⁵⁶        | Mobile health application       | UTAUT    | Portugal    | Users                   | 394         | No           |        |
| Duarte and Pinho⁵⁹    | Mobile health application       | UTAUT2   | Portugal    | Users                   | 120         | No           |        |
| Alam et al.⁶¹         | Mobile health app               | UTAUT2   | Bangladesh  | Young users             | 400         | Yes          | 0.11** |
| Cocosila and Archer⁶³ | SMS                             | Self-dev. Model | Canada  | Users                   | 50          | No           |        |
| Deng et al.³⁹         | Mobile health service           | TPB      | China       | Older and middle-age residents | 424   | No           |        |
| Schuster et al.⁶⁸     | Mobile electronic medical record| UTAUT    | South Korea | Professionals           | 449         | Yes          | 0.10*  |
|                       | Mobile health service           | TRA, TPB | France      | Consumers               | 482         | Yes          | 0.69*  |
|                       |                                 |          |             |                         |             |              | 0.67*  |
|                       |                                 |          |             |                         |             |              | 0.77*  |
| Cilliers et al.⁶⁹     | Mobile health information       | UTAUT    | South Africa| Students                | 202         | Yes          | 0.19*  |
|                       |                                 |          |             |                         | 6,188       |              |        |
| Sample size           |                                 |          |             |                         |             |              |        |
| Average of path coefficient |                                 |          |             |                         |             |              | 0.31   |

TAM: technology acceptance model; TPB: theory of planned behavior; TRA: theory of reasoned action; UTAUT: unified theory of acceptance and use of technology; UTAUT2: extended unified theory of acceptance and use of technology.

*p < 0.05. **p < 0.01.
Table 10. Articles examining the effect of FC on BI.

| Study            | Technology              | Theory    | Country     | Target group            | Sample size | Significant? | Beta   |
|------------------|-------------------------|-----------|-------------|-------------------------|-------------|--------------|--------|
| Dwivedi et al.¹  | Mobile health service   | UTAUT2    | USA         | Patients                | 1,125       | Yes          | 0.32*  |
|                  |                         |           | Canada      |                         |             |              | 0.39*  |
|                  |                         |           | Bangladesh  |                         |             |              | 0.31*  |
| Alam et al.³     | Mobile health application | UTAUT    | Bangladesh  | Generation Y consumers  | 296         | Yes          | 0.25*  |
| Hoque and Sorwar⁵ | Mobile health service   | UTAUT    | Bangladesh  | Elderly people          | 300         | No           |        |
| Zhang et al.⁴⁸   | Mobile health application | UTAUT    | China       | Patients                | 746         | Yes          | 0.17*  |
| Nunes et al.⁵⁶   | Mobile health application | UTAUT    | Portugal    | Users                   | 394         | No           |        |
| Lwin et al.⁵⁸    | Mobile health application | NR       | Sri Lanka   | Users                   | 404         | Yes          | 0.11*  |
| Duarte and Pinho⁵⁹ | Mobile health application | UTAUT2   | Portugal    | Users                   | 120         | No           |        |
| Alam et al.⁶¹    | Mobile health app       | UTAUT2    | Bangladesh  | Young users             | 400         | Yes          | 0.15***|
| Deng et al.³⁹    | Mobile health service   | TPB       | China       | Older and middle-age residents | 424    | Yes          | 0.20***|
|                  |                         |           |             |                         |             |              | 0.18***|
| Kim et al.⁶⁷     | Mobile electronic medical record | UTAUT | South Korea | Professionals           | 449         | Yes          | 0.27***|
| Schuster et al.⁶⁸ | Mobile health service   | TRA, TPB | France      | Consumers               | 482         | No           |        |
| Average of path coefficient |             |           |             |                         |             |              | 0.23   |

NR: not reported; TPB: theory of planned behavior; TRA: theory of reasoned action; UTAUT: unified theory of acceptance and use of technology; UTAUT2: extended unified theory of acceptance and use of technology.

* p < 0.05. ** p < 0.001.
Compared to other behavior-change models in healthcare science, the relationship between FC and BI was significantly positive in previous literature, see for example.\textsuperscript{12,35,71} However, one study\textsuperscript{72} investigated the adoption of fitness watches in China and empirically disproved this relationship. This finding can be attributed to fitness watches not requiring many resources from users; thus, the importance of FC was reduced. Furthermore, FC was examined in a small number of studies (11 studies), and this can be explained by FC not being included in many technology acceptance theories such as the TRA, the TAM, the TAM2, and the TAM3. Therefore, more research studies are needed in order to understand the effect of FC on the use of mHealth.

The results in Table 10 reveal that, across all mHealth types, the average path coefficient value of the seven articles is 0.23. According to the guidelines suggested in Cohen,\textsuperscript{38} the effect of FC on BI is medium. Therefore, the relationship between FC and BI is included in the general model for the acceptance of mHealth (see Figure 2).

**Attitude toward behavior**

Attitude toward behavior (ATB) can be described as a user’s positive or negative belief about using a certain technology.\textsuperscript{65} The theory of reasoned action suggests that ATB can be impacted by previous beliefs and results.\textsuperscript{70} In other words, the better outcomes a user expects from using a certain behavior, the more positive attitude he or she has. The meaning of ATB is similar to other constructs, such as intrinsic motivation in the motivational model, affect toward use in the MPCU and affect in SCT.\textsuperscript{26} Attitude toward behavior has been demonstrated to be a predictor of user behavior in various technology acceptance models, such as the TRA, the TPB, the TAM, and the A-TAM. Although a later version of the TAM excludes ATB, this is attributed to its weak mediation of the influence of PU on BI.\textsuperscript{21}

Regarding our review, out of 49 articles selected in this study, the effect of ATB on BI was examined in six, and five (83\%) of these found a significant positive relationship between the two factors (see Table 11). The results in Table 11 reveal that, across all mHealth types, the average path coefficient value of the five articles is 0.40. According to the guidelines suggested in [39], the effect of ATB on BI is medium. Therefore, the relationship between ATB and BI is included in the general model for the acceptance of mHealth (see Figure 2).

Our findings indicate that the relationship between ATB and BI is stronger than the other predictors in the proposed model. This outcome suggests that user ATB plays a highly effective role in driving the acceptance of mHealth. This result is consistent with another study, which investigated the acceptance of mHealth services among middle-aged and older residents in China.\textsuperscript{39} Their study found that ATB is the strongest predictor of BI among both groups. Similarly, it has been demonstrated that ATB is the most significant determinant of BI when compared with SN and FC.\textsuperscript{67}

**Behavioral intention**

The factor of BI is well documented in many technology acceptance models, such as the TRA, the TPB, the TAM, the TAM2, the A-TAM, the TAM3, the model of PEOU determinants, the UTAUT, and the UTAUT2. This inclusion indicates that BI is an important predictor for user acceptance of new technologies. Behavioral intention refers to an individual’s aim or plan to perform a specific behavior.\textsuperscript{65} In the context of mHealth usage, BI can be described as the aim or plan to use mHealth technology.

In accordance with previously developed models, existing studies on mHealth have proposed that BI is the only determinant of AB and can provide evidence of a user’s willingness to use
| Study          | Technology                                      | Theory          | Country    | Target group                      | Sample size | Significant | Beta   |
|---------------|-------------------------------------------------|-----------------|------------|-----------------------------------|-------------|-------------|--------|
| Tsai et al.18 | Telehealth                                      | TAM, IDT, SQB   | Taiwan     | Patients                          | 281         | Yes         | 0.55***|
| Hung and Jen  | Mobile health management system                  | TAM             | Taiwan     | Students                          | 170         | Yes         | 0.60** |
| Deng et al.39 | Mobile health service                            | TPB             | China      | Older and middle-age residents    | 424         | Yes         | 0.56***|
| Kim et al.67  | Mobile electronic medical record                 | UTAUT           | South Korea| Professionals                      | 449         | Yes         | 0.57***|
| Schuster et al.68 | Mobile health service                             | TRA, TPB       | France     | Consumers                         | 482         | Yes         | 0.21*  |
|               |                                                 |                 |            |                                   |             |             | 0.20*  |
| Sample size   |                                                 |                 |            |                                   |             |             | 0.15*  |
| Average of path coefficient |                                               |                 |            |                                   | 1,806       |             | 0.40   |

IDT: innovation diffusion theory; SQB: status quo bias; TAM: technology acceptance model; TPB: theory of planned behavior; TRA: theory of reasoned action; UTAUT: unified theory of acceptance and use of technology.

*p < 0.05. **p < 0.01. ***p < 0.001.
mHealth technology.\textsuperscript{1,3,5,55} Out of 49 articles selected in this study, the relationship between BI and AB was examined in seven, and all these found a significant positive relationship between the two factors (see Table 12). The results in Table 12 reveal that, across all mHealth types, the average path coefficient value of the seven articles is 0.45. According to the guidelines suggested in Cohen,\textsuperscript{38} the effect of BI on AB is high. Therefore, the relationship between BI and AB is included in the general model for the acceptance of mHealth (see Figure 2).

\textbf{Implications}

Based on the presented results, this study provides both theoretical and practical implications for practitioners. Theoretically, the acceptance of mHealth has been investigated using technology acceptance models by researchers (see the Appendix), which contributed to the increase in the number of technology acceptance models. To mitigate the confusion caused by the inconsistent results generated from these models, this study proposes a general model that could be used for all types of mHealth applications in various contexts. Furthermore, most studies on mHealth acceptance have employed the original constructs of previously developed technology acceptance models, such as the TAM and the UTAUT.\textsuperscript{5} This current research advances the theory by proposing a novel model and integrating the most commonly used significant relationships to explain the acceptance of mHealth. Our findings indicate that the most effective predictors in driving the acceptance of mHealth are PEOU, PU, SN, FC, and ATB. These results offer promise for integrating several factors into a model to predict the acceptance of mHealth in various contexts. In addition, our work reveals that the relative influence of the selected determinants on the acceptance of mHealth differs from one determinant to another. This finding implies that not all determinants are equally significant in driving the acceptance of mHealth. More accurately, while this current research illustrates the importance of five determinants on the acceptance of mHealth, the findings indicate that ATB is the strongest determinant, and FC is the weakest. Consequently, this paper recommends integrating several factors to understand further the predictors that drive the acceptance of mHealth. Moreover, the proposed model was developed using a generic approach that could be easily modified to examine the acceptance of mHealth in accordance with the target context.

On the other hand, the results of this research provide practical implications for practitioners to improve the acceptance of mHealth. While the findings demonstrate the importance of five predictors on the acceptance of mHealth, namely PEOU, PU, SN, FC, and ATB, PU is the most commonly used significant predictor for the acceptance of mHealth. As a result, if the usefulness of mHealth types is not established, users will avoid them and search for a more useful technology. Therefore, practitioners should pay more attention to the functionality and practicality of mHealth. Furthermore, our findings indicate that ATB is the most important determinant, with a strong influence on BI. This factor suggests that attitude toward mHealth augments user BI, which, in turn, attracts more individuals to use mHealth. In this regard, decision-makers should dedicate more consideration toward user attitude when addressing the acceptance of mHealth. Finally, for researchers, despite the number of studies that have investigated the acceptance of mHealth (see the Appendix), most reviewed studies were mainly conducted in three geographical areas: China, Taiwan, and Bangladesh. Other geographical territories, such as the Middle East and the Arab world, are considered to be under-researched. This factor might explain the low uptake of mHealth in those geographical regions.\textsuperscript{73} Therefore, special attention should be paid to investigate and analyze user requirements and to identify the factors that drive the acceptance of mHealth in those geographical regions, which, in turn, will contribute to the uptake of mHealth. Moreover, the differences in the acceptance of mHealth based on demographic characteristics can be studied to explain more profoundly the decision to use mHealth services among various segments.
Table 12. Articles examining the effect of BI on AB.

| Study           | Technology                  | Theory    | Country     | Target group      | Sample size | Significant? | Beta       |
|-----------------|-----------------------------|-----------|-------------|-------------------|-------------|--------------|------------|
| Dwivedi et al.  | Mobile health service       | UTAUT2    | USA         | Patients          | 1,125       | Yes          | 0.67*      |
|                 |                             |           | Canada      |                   |             |              | 0.72*      |
|                 |                             |           | Bangladesh  |                   |             |              | 0.76*      |
| Alam et al.     | Mobile health app           | UTAUT     | Bangladesh  | Generation Y consumers | 296       | Yes          | 0.29*      |
| Hoque and Sorwar| Mobile health service       | UTAUT     | Bangladesh  | Elderly people    | 300         | Yes          | 0.42*      |
| Dou et al.      | Mobile health app           | TAM       | China       | Patients           | 157         | Yes          | 0.10*      |
| Hoque           | Mobile health service       | UTAUT     | Bangladesh  | Students           | 227         | Yes          | 0.82*      |
| Alam et al.     | Mobile health app           | UTAUT2    | Bangladesh  | Young users        | 400         | Yes          | 0.17*      |
| Kissi et al.    | Telehealth                  | TAM       | Ghana       | Physicians         | 543         | Yes          | 0.09*      |
| Sample size     | 3,048                       |           |             |                   |             |              |            |
| Sample size     | 3,048                       |           |             |                   |             |              | 0.45       |

TAM: technology acceptance model; UTAUT = unified theory of acceptance and use of technology; UTAUT2: extended unified theory of acceptance and use of technology. 
*<i>p < 0.05</i>.
Limitations and recommendations

This research, as with other review studies, is not free of limitations. First, this work was conducted with the objective of systematically reviewing prior studies on the acceptance of mHealth to identify the most commonly used significant relationships based on peer-reviewed articles published in scientific journals. The authors considered this procedure to ensure the quality of the selected articles. Future reviews could include other content types, such as conference proceedings, reports and dissertations.

In addition, the time span of article eligibility in this study is 10 years. Considering that innovations have been changing rapidly over the past 10 years and the probability of considerable innovative differences in the near future, researchers should be cautious when using the results of this work. Understanding how innovative developments might affect user BI regarding mHealth is an option for future researchers.

Finally, this study proposes a general model for the acceptance of mHealth based on a systematic review of literature published on mHealth. Having proposed the general model, further investigation could be conducted to examine empirically the reliability and validity of the developed model by collecting data from users. This aspect is especially important to demonstrate the explanatory power and fit of the proposed model. In addition, future researchers may conduct a qualitative study for model validation using expert panels and study their agreement indexes.

Conclusion

Despite the large number of mHealth applications available for users, this does not necessarily ensure user uptake. As such, the objectives of this paper were (1) to systematically review related articles within the domain of mHealth acceptance; (2) to identify the most commonly used significant relationships among these articles; (3) to address the strength of the identified relationships; and (4) to propose a general model with its latent constructs to understand the acceptance of mHealth.

This paper analyzed 49 recent research articles on mHealth acceptance published in scientific journals during the past 10 years. These articles examined 100 constructs, 26 dependent variables and 170 relationships. The review identified seven relationships (PU → BI, PEOU → BI, PEOU → PU, SN → BI, FC → BI, BI → AB, and ATB → BI) as the most commonly used significant relationships in the selected articles. Our general model is proposed based on the average path coefficient and significance level, addressing the key determinants for the acceptance of mHealth.

The findings reveal that the most commonly used predictor for the acceptance of mHealth is PU (36 times), followed by PEOU (30 times), SN (16 times), FC (12 times), and ATB (10 times). Furthermore, the strongest predictor for the acceptance of mHealth is ATB (β = 0.40), followed by PEOU (β = 0.35), PU (β = 0.33), SN (β = 0.31), and FC (β = 0.23). These results are summarized in the general model for the acceptance of mHealth, as depicted in Figure 2.

Acknowledgements

The authors, therefore, gratefully acknowledge DSR technical and financial support.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.
Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This project was funded by the Deanship of Scientific Research (DSR), King Abdulaziz University, Jeddah, under grant no. J: 57-156-1441.

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## Appendix A

Table A1. Papers included in the meta-analysis.

| Study                  | Technology                  | Theory base | Country                        | Target group               | Sample size |
|------------------------|-----------------------------|-------------|--------------------------------|-----------------------------|-------------|
| Dwivedi et al.          | Mobile health service       | UTAUT2      | USA, Canada, Bangladesh        | Patients                    | 1,125       |
| Alam et al.             | Mobile health application   | UTAUT       | Bangladesh                     | Generation Y consumers     | 296         |
| Zhang et al.            | Mobile health service       | TAM         | China                          | Users                       | 650         |
| Hoque and Sorwar        | Mobile health service       | UTAUT       | Bangladesh                     | Elderly people              | 300         |
| Chen et al.             | Mobile health application   | Self-developed | China                      | App users                   | 284         |
| Sezgin et al.           | Mobile health application   | TAM         | Turkey                         | Physicians                  | 122         |
| Chang et al.            | Mobile health information   | TPB, SCT    | Singapore                      | Women                       | 1,878       |
| Cho                    | Mobile health application   | TAM         | Korea                          | Students                    | 343         |
| Hossain                | Mobile health service       | IS Success  | Bangladesh                     | Users                       | 199         |
| Dou et al.              | Mobile health application   | TAM         | China                          | Patients                    | 157         |
| Tsai et al.             | Telehealth                  | TAM, IDT, SQB | Taiwan                      | Patients                    | 281         |
| Sezgin et al.           | Mobile health application   | TAM         | Turkey                         | Physicians                  | 151         |
| Deng et al.             | Mobile health service       | TPB         | China                          | Older and middle-age residents | 424         |
| Zhou et al.             | Telehealth                  | TAM         | China                          | Elderly people              | 436         |
| Miao et al.             | Mobile health service       | TAM         | China                          | Older and middle-age patients | 519         |
| Xue et al.              | Mobile health application   | TAM         | Singapore                      | Elderly women               | 700         |
| Hung and Jen            | Mobile health management system | TAM     | Singapore                      | Students                    | 170         |
| Guo et al.              | Mobile health service       | TAM         | China                          | Elderly consumers           | 204         |
| Kuo et al.              | Mobile electronic medical record | TAM     | Taiwan                         | Nurses                      | 665         |
| Liu and Cheng           | Mobile electronic medical record | TAM     | Taiwan                         | physicians                  | 158         |
| Beldad and Hegner       | Mobile health application   | TAM         | Germany                         | Users                       | 476         |
| Zhang et al.            | Mobile health application   | UTAUT       | China                          | Patients                    | 746         |
| Lim et al.              | Mobile web app              | TAM         | Singapore                      | Students, staff             | 164         |
| Hoque                  | Mobile health service       | UTAUT       | Bangladesh                     | Students                    | 227         |
| Nunes et al.            | Mobile health application   | UTAUT       | Portugal                        | Users                       | 394         |
| Zhu et al.              | Mobile health management system | TAM     | China                          | Patients                    | 279         |
| Lwin et al.             | Mobile health application   | Self-developed | Sri Lanka                  | Users                       | 404         |

(Continued)
| Study                  | Technology                        | Theory base  | Country  | Target group | Sample size |
|-----------------------|-----------------------------------|--------------|----------|--------------|-------------|
| Duarte and Pinho       | Mobile health application         | UTAUT2       | Portugal | Users        | 120         |
| Deng et al.            | Mobile health application         | TAM          | China    | Patients     | 388         |
| Alam et al.            | Mobile health app                 | UTAUT2       | Bangladesh | Young users | 400         |
| Cocosila and Archer    | SMS                               | Self-developed | Canada  | Users        | 50          |
| Kissi et al.           | Telehealth                        | TAM          | Ghana    | Physicians   | 543         |
| Kim et al.             | Mobile electronic medical record  | UTAUT        | South Korea | Professionals | 449         |
| Schuster et al.        | Mobile health service             | TRA, TPB     | France   | Consumers    | 482         |
| Cilliers et al.        | Mobile health information         | UTAUT        | South Africa | Students   | 202         |
| Liu et al.             | Mobile health service             | Motivation theory | China  | Residents    | 241         |
| Leung and Chen         | Mobile health application         | ECM          | China    | Residents    | 1,007       |
| Guo et al.             | Mobile health service             | Self-developed | China   | Consumers    | 650         |
| Wang et al.            | Mobile health service             | TAM          | China    | Customers    | 217         |
| Cocosila               | Mobile health application         | Motivation theory | UK      | Smokers      | 170         |
| Mburu and Oboko        | SMS                               | Self-developed | Kenya   | Patients     | 73          |
| Bandyopadhyay et al.   | SMS                               | TAM          | Ethiopia | Students     | 390         |
| Okazaki et al.         | Mobile health monitor             | Self-developed | Japan   | Physicians   | 471         |
| Cho et al.             | Mobile health application         | TAM          | USA      | Students     | 408         |
| Zhang et al.           | Mobile health service             | TRA          | China    | Customers    | 481         |
| Lee and Han            | Mobile health service             | Self-developed | South Korea | Consumers | 550         |
| Kwon et al.            | Mobile health application         | Self-developed | USA     | Students     | 391         |
| Balapour et al.        | Mobile health application         | Self-developed | Israel  | Patients     | 292         |
| Hsiao and Chen         | Mobile health systems             | ECM          | Taiwan   | Professionals | 201         |