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SPECIAL FOCUS PAPER

Mobile Health for Biomedical and Economic Intelligence: An Integrated Adoption Model for Young Adults

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ABSTRACT

Mobile health (m-health) has become an important component of digital healthcare delivery, yet its long-term value depends not only on technical usability but also on user adoption patterns that influence scalability, resource efficiency, and sustainable service design. Using a hybrid of Theory of Planned Behaviour (TPB), the technology acceptance model (TAM), Dual Factor Theory, and trust, we developed a model to examine the determinants of m-health adoption among young adults in Asia during and post-COVID-19. Our evidence is based on an online survey of 390 respondents aged 20–39 who reported that behavioural, technological, and psychological factors shape adoption intentions and reflect on biomedical intelligence and personalised treatment plans. Variables such as attitude and subjective norm were found to be most influential on the adoption decision for m-health services. Systems trust and resistance to change also enhanced the rate of adoption. Attitude emerges as the most significant factor, while perceived ease of use and perceived usefulness exert indirect effects on attitude. Subjective norm, trust, and resistance to change significantly impact the perceived usefulness for both users and healthcare providers. Based on these results, it can be stated that increasing trust, focusing on users' needs and values, and developing cost-efficient and personalised m-health solutions are key elements. Our study also confirms that system trust enhances the biomedical intelligence, early diagnosis of fatal diseases, and biomedical innovation.

KEYWORDS

mobile health (m-health), m-health adoption, biomedical intelligence, technology acceptance, trust, resistance to change, structural equation modelling

1 INTRODUCTION

The advent of the COVID-19 crisis has accelerated the shift of healthcare encounters from real-world settings to virtual and mobile spaces. While the urgent situation

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brought about by the pandemic is no longer present, there remains a need for a resilient, scalable, and user-orientated healthcare system. The concept of m-health, which refers to the provision of health services via mobile devices, provides a tangible pathway for remote consultation, monitoring, aftercare, medication management, and patient-provider communication [1]–[4]. For health systems facing workforce limitations, uneven access to services, and growing demand for chronic disease management, m-health is no longer a peripheral convenience. It has become part of the infrastructure through which patients, providers, and health organisations exchange timely information.

The present study links m-health adoption with biomedical intelligence. In this paper, biomedical intelligence refers to the practical use of trusted, timely, user-generated and system-generated health data to support monitoring, decision support, personalised care pathways, and preventive health behaviour. M-health services are crucial in this regard, as they can provide continuous information on health behaviour, symptoms, appointments, and self-management. Nevertheless, all these benefits hinge upon users' readiness to use m-health services. A technically capable application will not support biomedical intelligence if users do not trust it, do not perceive it as useful, or resist changes to familiar healthcare routines. Young adults are a particularly relevant population for examining m-health adoption. They always have access to smart devices and digital services, but reliance on healthcare services cannot depend solely on them. The choice to use these services can be influenced by their perceived usefulness, usability, social influence, trust issues, and unwillingness to change their behaviour of seeking health services. In China and comparable Asian digital health contexts, the post-pandemic expansion of mobile platforms has created new opportunities for patient engagement while also raising questions about which factors encourage or inhibit adoption [5]–[8]. Existing literature has made substantial progress in explaining digital health acceptance, but several gaps remain. First, many studies rely on positive adoption factors, especially perceived usefulness and perceived ease of use, while giving less attention to inhibitors such as resistance to change and privacy/security concerns. Second, older adults and healthcare professionals have attracted considerable attention, whereas young adults have received comparatively less integrated analysis. Third, m-health adoption research often applies the technology acceptance model (TAM), Theory of Planned Behaviour (TPB), or user resistance perspectives separately, even though actual adoption is likely shaped by both enabling and inhibiting forces. Fourth, trust remains essential in digital healthcare because users must believe that systems provide reliable information and perform as promised, yet trust is often treated as secondary rather than central [9]–[13]. To address these gaps, this study develops and tests an integrated m-health adoption model based on TAM, TPB, Dual-Factor Theory, and trust. TAM contributes perceived usefulness, perceived ease of use, and attitude. TPB contributes subjective norm and perceived behavioural control. Dual-Factor Theory contributes the distinction between enablers and inhibitors, represented here through resistance to change and privacy/security concerns. Trust is incorporated as a digital health-specific determinant of perceived usefulness and behavioural intention. The study therefore asks: Which behavioural, technological, social, trust-based, and resistance-related factors explain young adults' intention to use m-health services? How do enabling and inhibiting factors operate together in a post-pandemic digital healthcare context?

The study makes three contributions. Theoretically, it integrates acceptance and resistance perspectives to provide a more balanced explanation of m-health adoption. Methodologically, it validates the proposed model using survey data from 390 young adults and structural equation modelling. In practice, it would assist developers, healthcare professionals, and policymakers in focusing on the problems

associated with the design and management of the m-health system, with a view to making it more widely used and medically valuable. The following sections of the paper discuss the literature review, research model and hypotheses, methodology, results, implications, and conclusions with research limitations and directions.

2 LITERATURE REVIEW

2.1 Mobile health (m-health) and biomedical intelligence

The use of ICTs has transformed healthcare provision by enabling the capture, storage, processing, and sharing of health information electronically [14], [15]. M-health is an extension of e-health, incorporating health information services via mobile devices such as cell phones, tablets, monitors, and personal digital assistants. Its value lies in mobility, immediacy, and the ability to connect users with health resources beyond fixed clinical locations [2], [4]. From the perspective of biomedical intelligence, m-health is important because data generated through mobile interactions could enhance healthcare responsiveness. Appointment data, consultations, symptoms, exercises, medications, and sensor data may help improve patient care decisions, provided the data is reliable, interoperable, and appropriately managed. However, the transformation of data collected by mobile devices into biomedical intelligence is not automatic.

2.2 Patient- and provider-focused m-health applications

Applications for m-health can generally be categorised based on two broad types: those intended for providers and those intended for patients. The former encompasses access for point-of-care, emergency services, patient documentation, e-prescribing, and decision-making tools [16]–[18]. The integration of these applications with other health information systems can facilitate improved coordination, reduce delays, and enhance clinical preparedness. The latter includes glucose monitoring, heart rate monitoring, wellness planning, diet management, maternity assistance, drug administration, and teleconsultations [19]–[22]. Teleconsultation websites have become very popular in the past few years, especially during the pandemic, due to their ability to offer consultations when physical access is limited. Nevertheless, such applications require more than just functionality to be truly effective.

2.3 Technology adoption in digital health

Research on m-health adoption has examined healthcare workers, hospitals, older adults, patients, and general users [8], [23]–[26]. The literature shows that perceived usefulness, ease of use, trust, social influence, and behavioural control can shape users' intention to adopt digital health systems. At the same time, resistance, privacy concerns, and lack of fit with established care routines can reduce adoption [12], [27], [28]. A key limitation in this literature is that adoption is often framed as a positive acceptance process. In digital healthcare, however, users can simultaneously recognise the benefits and feel hesitant to change familiar medical practices. M-health adoption, therefore, requires a model capable of explaining both attraction and hesitation. This is especially relevant for young adults, who may be digitally competent yet cautious about replacing face-to-face medical interactions with mobile services.

2.4 TAM, TPB, dual-factor theory, and trust

The technology acceptance model explains acceptance of technology through perceived usefulness, perceived ease of use, attitude, and behavioural intention [29]. Regarding m-health technology, perceived usefulness refers to users' belief that mobile technology will help them achieve convenience, quality of life, effectiveness, or efficiency. Ease of use is the system's simplicity in learning and using the technology. This is important for health technology acceptance because the technology should help people reduce the burden [11], [30]. The TPB utilises attitude, subjective norm, and perceived behavioural control to elucidate intention [31], [32]. The subjective norm is particularly important when family, friends, and other trusted social figures influence health-related decision-making. Perceived behavioural control assesses the extent to which an individual believes they possess the resources and capabilities required to perform the behaviour.

The Dual-Factor Model includes a valuable adjustment in recognising the difference between enabling factors and inhibiting factors [33]. Enabling factors may motivate users to adopt the technology; however, the lack of an enabling factor does not imply a resistive factor. Inhibiting factors, such as resistance to change or privacy/security issues, may reduce users' likelihood of adopting the technology despite their awareness of its advantages. It is necessary to give due consideration to trust in m-health as well [12], [13].

3 RESEARCH MODEL AND HYPOTHESES

The proposed framework, illustrated in Figure 1, combines elements from the TAM, TPB, Dual-Factor Theory, and trust. TAM provides insights into perceived usefulness, perceived ease of use, and overall attitude. TPB includes factors such as subjective norm and perceived behavioural control. Dual-Factor Theory addresses resistance to change and concerns regarding privacy and security. Trust is included because users of m-health applications need to assess not just the system's usability but also the trustworthiness of the information and its functional reliability. Within this framework, attitude is anticipated to directly influence behavioural intention, as individuals who view m-health positively are more inclined to use it. It is expected that perceived usefulness and perceived ease of use will shape attitude, with perceived ease of use also enhancing perceived usefulness.

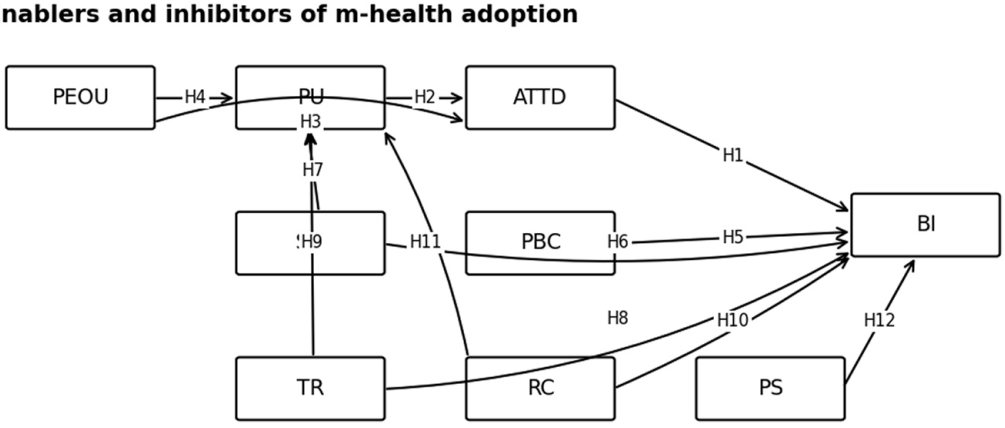


Fig. 1. Proposed integrated m-health adoption model

The subjective norm is expected to directly influence behavioural intention and indirectly affect perceived usefulness by shaping users' perceptions of the benefits of transitioning to mobile services. Conversely, trust is predicted to have a positive effect on both behavioural intention and perceived usefulness, as reliable systems are typically viewed as beneficial. On the inhibiting side, the model acknowledges that even the young generation could reject m-health if it interferes with their existing practices of health care management and communication with doctors. In this case, resistance to change is supposed to negatively affect both behavioural intention and perceived usefulness. Privacy and security concerns are also expected to reduce behavioural intention because m-health systems process sensitive personal and health information. All these assumptions have been summarised in Table 1 to guide the fieldwork and data collection.

Table 1. Research hypotheses

Hypothesis	Statement
H1	A positive attitude significantly influences young adults' intention to use m-health services.
H2	The perceived usefulness of m-health services positively influences young adults' attitudes toward using them.
H3	The perceived ease of use of m-health services positively influences young adults' attitudes toward using them.
H4	The ease of use a user perceives positively influences their perception of a product or system's usefulness.
H5	Perceived behavioural control positively influences young adults' intentions to use m-health services.
H6	The subjective norm positively influences young adults' intention to use m-health services.
H7	The subjective norm has a positive effect on perceived usefulness.
H8	Trust positively impacts the intention to use m-health services.
H9	Trust positively affects how useful people perceive something to be.
H10	Resistance to change negatively affects individuals' intention to use m-health services.
H11	Resistance to change negatively affects how useful something is perceived.
H12	Concerns about privacy and security negatively affect people's intention to use m-health services.

4 METHODOLOGY

4.1 Research design

The study employed a quantitative survey design to investigate the relationships among the constructs in the integrated m-health adoption model. A quantitative approach was suitable because the constructs had been clearly defined in advance and were tested using numerical data and structural modelling. The design focused on behavioural intention rather than actual use, as m-health adoption remains inconsistent. Moreover, behavioural intention is a recognised predictor in adoption research. This study was conducted with ethical clearance from Salford University (ID number 17417).

4.2 Data collection and sample

Data were collected through an online survey of 390 young adults aged 20 to 39 years. The sample comprised 171 males (43.8%) and 219 females (56.2%), indicating a slightly higher representation of female participants. In terms of age distribution, the largest group of respondents was aged 20–24 years, making up 43.1% of the sample. Participants aged 25–29 accounted for 34.4%, while those aged 30–34 comprised 17.9%. The smallest group comprised respondents aged 35–39, representing only 4.6% of the total sample. This distribution indicates that the study primarily reflects the perspectives of younger adults, who are generally more familiar with mobile technologies and digital health applications.

4.3 Measurement instrument

The survey included questions adapted from reliable research on TAM, TPB, trust, resistance to change, privacy and security, and behavioural intention. All responses to the questions were given on a scale ranging from 1 to 5. The survey included indicators of attitude, usefulness, usability, behavioural control, subjective norms, trust, resistance to change, privacy/security, and behavioural intention. Pre-testing involved testing of items on 12 respondents to determine their appropriateness and consistency. All the constructs and measurements are presented in Table 2.

Table 2. Constructs and retained measurement items

Construct	Retained Items After EFA	Source Basis
ATTD	ATTD1-ATTD3	TAM and adoption literature [29], [34]
PU	PU1-PU3, PU5, PU4 excluded	TAM and health technology studies [29], [35]
PEOU	PEOU1, PEOU2, PEOU4, PEOU3 excluded	TAM and m-health studies [29], [36]
PBC	PBC1-PBC3	TPB-based adoption research [31], [34]
SN	SN1-SN3	TPB and social influence research [31], [37]
TR	TR1-TR3	Trust in digital health [12], [13]
RC	RC1, RC3, RC4, RC2 excluded	Dual-factor and resistance literature [27], [33]
PS	PS1-PS3	Privacy/security literature [12], [13]
BI	BI1-BI3	Technology adoption literature [29]

4.4 Data analysis procedure

SPSS was utilised to conduct descriptive statistics, assess reliability, and perform exploratory factor analysis. Cronbach's alpha values were calculated to evaluate internal consistency. The content validity of the scale was established by integrating items from previous studies, while construct validity was confirmed through exploratory factor analysis using principal component analysis (PCA). AMOS was employed to assess the structural equation model, evaluate goodness of fit, and test the proposed relationships. A p-value of less than 0.05 was used to indicate statistical support for the hypotheses.

5 RESULTS

5.1 Respondent profile

As shown in Table 3, the demographic profile of respondents included more female than male respondents and was concentrated in the 20–29 age range. The education profile indicates a highly educated sample, which is relevant when interpreting non-significant perceived behavioural control effects, as many respondents may already have the resources and capabilities required to use mobile services.

Table 3. Demographic profile of respondents

Variable	Category	Frequency	Percentage
Gender	Male	171	43.8%
	Female	219	56.2%
Age	20–24	168	43.1%
	25–29	134	34.4%
	30–34	70	17.9%
	35–39	18	4.6%
Education	Bachelor's degree	202	51.8%
	Master's degree	141	36.2%
	Doctoral degree	35	9.0%
	Other	12	3.0%
Total		390	100%

5.2 Reliability and validity

The reliability analysis revealed acceptable to high internal consistency across the various constructs. Cronbach's alpha scores ranged from 0.753 to 0.885, while the construct reliability score was 0.826. This indicates that the outcomes exceed the acceptable threshold of 0.70. See Table 4 that shows all reliability results.

Table 4. Reliability results

Construct	Cronbach's Alpha	Items	Evaluation
Attitude	0.885	3	High
Perceived usefulness	0.877	5	High
Perceived ease of use	0.753	4	Acceptable/high
Perceived behavioural control	0.865	3	High
Subjective norm	0.876	3	High
Trust	0.884	3	High
Resistance to change	0.795	4	Acceptable/high

(Continued)

Table 4. Reliability results *(Continued)*

Construct	Cronbach's Alpha	Items	Evaluation
Privacy and security	0.825	3	High
Behavioural intention	0.846	3	High
Overall constructs	0.826	31	High

5.3 Exploratory factor analysis

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.894, indicating good adequacy. Bartlett's test of sphericity revealed a significant test result, with an approximate chi-square value of 7332.266, 465 degrees of freedom, and a p-value of 0.000. This suggests that factor analysis is appropriate for the data. PCA was performed to extract nine components, which explained 74.738% of the variance. The Rotated Component Matrix indicated that items PU4, PEOU3, and RC2 did not load properly and were therefore eliminated. The refined measurement structure demonstrated acceptable construct validity for subsequent structural equation modelling (SEM) analysis. Table 5 presents a summary of the valdity and exploratory factor analysis.

Table 5. Validity and exploratory factor analysis summary

Indicator	Result	Interpretation
KMO	0.894	Sampling adequacy is meritorious
Bartlett's test	$\chi^2 = 7332.266$; df = 465; p = .000	Correlation matrix suitable for EFA
Components extracted	9	Aligned with model constructs
Cumulative explained variance	74.738%	Adequate explanatory power
Excluded items	PU4, PEOU3, RC2	Removed due to inadequate loading

5.4 Structural model fit

Based on the SEM analysis, the model showed a good fit. This is because the relative chi-square was less than 3, the RMSEA was below 0.08, and CFI, GFI, TLI, and IFI were above 0.90. From this, one can conclude that the model was adequate for explaining the covariances.

Table 6. Structural model fit indices

Fit Index	Obtained Value	Recommended Threshold	Interpretation
χ^2	541.015	Lower preferred	Acceptable with df considered
df	323	>0	Acceptable
χ^2/df	1.675	<3	Good
CFI	0.968	>0.90	Good
GFI	0.914	>0.90	Good
RMSEA	0.042	<0.08	Good
TLI	0.963	>0.90	Good
IFI	0.969	>0.90	Good

Figure 2 shows that the structural equation model provides an appropriate description of the relationships among the variables considered in the research. Such conclusions are also supported by the outcomes demonstrated in Table 6, which show that all major measures of the goodness-of-fit exceed generally accepted standards. First of all, χ^2/df equal to 1.675 proves a good fit between the model and data, while CFI equal to 0.968, GFI equal to 0.914, TLI equal to 0.963, and IFI equal to 0.969 provide evidence for the high explanatory power of the model. Besides, a small value of RMSEA equal to 0.042 implies a negligible model misspecification.

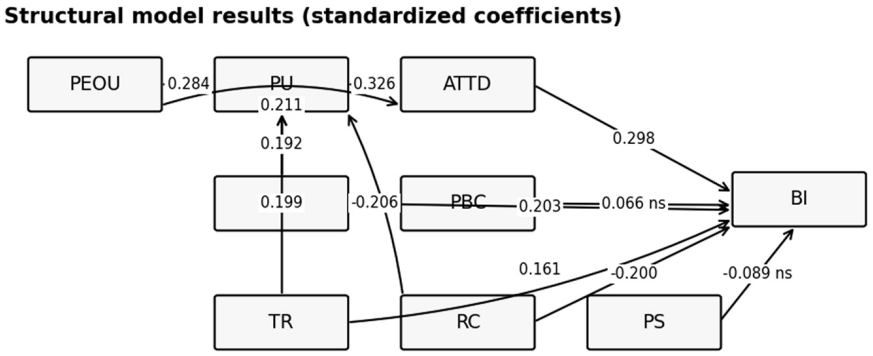


Fig. 2. Structural equation model results

Notes: Model fit: χ^2/df = 1.675; CFI = 0.968; GFI = 0.914; RMSEA = 0.042; TLI = 0.963; IFI = 0.969.

5.5 Hypothesis testing

The test results for the hypotheses are summarised in Table 7 below. Out of 12 tested hypotheses, 10 received support. The greatest contribution to behavioural intention came from attitude (β = 0.298, p < 0.05), followed by subjective norm (β = 0.203), trust (β = 0.161), and resistance to change (β = –0.200). Additionally, perceived usefulness significantly influenced attitude (β = 0.326), while perceived ease of use affected both attitude (β = 0.211) and perceived usefulness (β = 0.284).

Table 7. Hypothesis testing results

H	Path	β	S.E.	C.R.	p	Result
H1	BI ← ATTD	0.298	0.051	5.684	***	Supported
H2	ATTD ← PU	0.326	0.063	5.556	***	Supported
H3	ATTD ← PEOU	0.211	0.058	4.807	***	Supported
H4	PU ← PEOU	0.284	0.053	3.642	***	Supported
H5	BI ← PBC	0.066	0.062	1.142	0.253	Not supported
H6	BI ← SN	0.203	0.048	3.431	***	Supported
H7	PU ← SN	0.192	0.046	3.322	***	Supported
H8	BI ← TR	0.161	0.056	2.724	0.006	Supported
H9	PU ← TR	0.199	0.054	3.407	***	Supported
H10	BI ← RC	–0.200	0.058	–3.509	***	Supported
H11	PU ← RC	–0.206	0.053	–3.769	***	Supported
H12	BI ← PS	–0.089	0.076	–1.597	0.110	Not supported

6 DISCUSSION

6.1 Adoption enablers: Attitude, usefulness and ease of use

The research findings show that attitude is the strongest direct predictor of behavioural intention to use m-health services. This suggests that young adults are more likely to adopt m-health when they evaluate mobile services as wise, pleasant, and personally desirable. Attitude appears to translate the technical qualities of m-health into a behavioural orientation toward use. In practical terms, m-health platforms must therefore offer value that users can recognise in ordinary health management, such as convenience, cost reduction, and improved access to information. Perceived usefulness significantly shaped attitude, while perceived ease of use influenced both attitude and perceived usefulness. This pattern supports the central logic of TAM. Young adults may be willing to explore mobile services, but favourable attitudes depend on whether the application appears to be practically beneficial and easy to use. A simple interface is not only a usability feature; it also strengthens perceived usefulness by making the system's benefits easier to access [38].

6.2 Social influence and trust in m-health acceptance

Subjective norm significantly influenced both behavioural intention and perceived usefulness. This suggests that recommendations or expectations from important social contacts may shape whether young adults see m-health as valuable. The finding should not be interpreted as cultural determinism, but it does show that adoption occurs within a social environment. For young users, the opinions of peers, family members, or trusted contacts may reduce uncertainty and strengthen confidence in m-health services. Trust also had significant effects on behavioural intention and perceived usefulness. This finding is important because m-health systems operate in a sensitive domain where users depend on accurate information and reliable functions. Systems with high credibility create positive expectations for outcomes, thereby making the service seem more useful. On the other hand, systems that are not well managed and are unreliable may hinder the use despite being functional [39].

6.3 Resistance to change as a behavioural inhibitor

Resistance to change negatively affected behavioural intention and perceived usefulness. This confirms the value of including inhibitor variables alongside adoption enablers. Even digitally capable young adults may hesitate to change familiar routines for consultation, self-care, or interaction with physicians. In healthcare, established practices may carry reassurance and legitimacy, especially when users prefer direct interaction for sensitive concerns. M-health design should therefore reduce disruption rather than simply replace traditional contact. The negative effect of resistance on perceived usefulness is particularly relevant. However, when m-health is seen as a challenge for established health management practices, users tend to ignore its benefits as well. Thus, in addition to being a behavioural barrier, resistance is a cognitive filter that influences the user's interpretation of usefulness.

6.4 Non-significant effects of perceived behavioural control and privacy/security

Perceived behavioural control did not significantly affect behavioural intention. One plausible explanation is that the sample consisted of young adults with high levels of education and likely access to smartphones and digital services. When users already possess the basic resources and capabilities to use m-health, perceived control may become less of a differentiating predictor. This does not mean control is unimportant for all populations; rather, its effect may be weaker among digitally capable groups.

Similarly, there was no significant impact of privacy and security concerns on the behavioural intention. The finding needs careful interpretation. The finding does not imply that privacy is irrelevant for m-health. Concerns might get normalised for users of mobile and social applications, or privacy might indirectly influence adoption via trust. From a governance perspective, privacy protection remains important, as m-health systems store personal and sensitive health data.

7 CONCLUSION

This study examined the determinants of m-health adoption among young adults using an integrated model that combines TAM, TPB, Dual-Factor Theory, and trust. Survey data from 390 respondents and SEM analysis indicate that attitude, subjective norm, trust, and resistance to change significantly influence the intention to adopt m-health services. Usefulness and perceived ease of use affect intention through attitude, whereas perceived behavioural control and privacy/security concerns are not significant predictors in this sample. The findings demonstrate the necessity of treating m-health technology adoption as more than a mere technical acceptance phenomenon. Although young people are technologically savvy, their decisions about m-health adoption are influenced by how useful, easy, socially approved, trusted, and consistent with existing practices they find this new technology. Resistance to change is a relevant barrier that needs to be overcome. The study contributes to digital health research by presenting and testing a balanced model of adoption enablers and inhibitors. It also contributes to biomedical intelligence by showing that the data value of m-health depends on sustained user participation. In post-pandemic healthcare, m-health can support more responsive and personalised services, but only if users trust the system and perceive the service as beneficial in everyday health management.

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