

Factors Influencing Users Adoption of M-Health Apps: A Literature Review

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DOI Link: <http://dx.doi.org/10.6007/IJAREMS/v15-i1/27558>

Published Online: 07 February 2026

Abstract

This literature review examines factors influencing users' adoption of M-Health apps, integrating psychological, technological, and behavioral perspectives with a focus on implications for the KSA. Drawing on Technology Acceptance Model (TAM), Technology Readiness and Acceptance Model (TRAM), Protection Motivation Theory (PMT), and related frameworks, the review synthesizes evidence on key antecedents perceived value, perceived usefulness, perceived ease of use, trust, health/e-health literacy, optimism, innovativeness, discomfort, insecurity, and health consciousness and their effects on behavioral intention and actual usage. It highlights implementation barriers such as usability, interoperability, privacy/security concerns, and uneven digital literacy that impede sustained engagement despite high smartphone penetration and national digital health initiatives. The review identifies significant research gaps: limited integration of dispositional and perceptual constructs, insufficient mediation and moderation analyses (notably the mediating role of behavioral intention and moderating effects of age), and sparse context-specific empirical work in Middle Eastern public health systems. Recommendations include adopting integrated TRAM-based models, employing longitudinal and mixed-methods designs, testing mediating/moderating mechanisms, and conducting intervention trials (usability redesigns, literacy programs, privacy transparency) to translate infrastructure investments into equitable, long-term M-Health adoption.

Keywords: M-Health Apps, Technology Adoption, Technology Readiness (TRAM), Perceived Usefulness, Trust And Privacy, Health Literacy, Behavioral Intention, KSA

Introduction

M-Health apps are now central to digital healthcare, enabling remote access, self-management, and ongoing patient engagement. Using mobile and wireless technologies, these apps support chronic disease care, prevention, health monitoring, and communication between patients and providers, improving access and efficiency (Marcolino et al., 2018; Triantafyllidis et al., 2019). Health systems worldwide including in the Middle East have woven M-Health into national digital strategies to raise service quality and promote patient-centered care (Wang & Qi, 2021; WHO, 2025).

Yet wider, sustained use of M-Health remains uneven. Research applying models such as TAM, UTAUT/UTAUT2, and technology-readiness frameworks finds that perceived usefulness, ease of use, trust, and supportive conditions forecast intention to use (Shemesh & Barnoy, 2020; Yang et al., 2025; Zhang et al., 2019). Many studies, however, examine single factors or take provider-focused perspectives, leaving the literature fragmented and limiting insight into how psychological, technological, and behavioural factors combine an important shortfall in high-risk healthcare settings where privacy and trust are decisive (Jacob et al., 2022; Wang & Qi, 2021).

This review brings those strands together and evaluates them for practical use. It surveys the main theoretical approaches, summarizes evidence on psychological drivers, technology readiness, and behavioural influences, and pinpoints gaps for future work. By combining global findings with Saudi-specific developments under Vision 2030 and national e-health efforts, the review offers a compact, theory-informed basis to guide research, design, and policy aimed at improving meaningful, long-term adoption of M-Health apps (Alessa et al., 2024; MOH., 2024).

Theoretical Foundations of M-Health Adoption

Understanding why people adopt M-Health apps draws on several established theories from psychology and information systems. Each offers constructs that help explain different facets of adoption attitudes and social influence, cognitive appraisals of usefulness and ease, dispositional readiness, and threat- or protection-related motivations. Below is a concise overview of the principal models used in M-Health research and their relevance.

1. Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB)

TRA links behavior to behavioral intention, which is shaped by attitudes and subjective norms (Ajzen & Fishbein, 1975). TPB adds perceived behavioral control (PBC) to capture perceived ability to perform the behavior under constraints (Ajzen, 1991). TPB is useful in health contexts because it brings social pressures and perceived capability into predictions of intention, but it does not explicitly model technology attributes (e.g., usability) or dispositional traits, so it is often combined with technology-specific frameworks.

2. Technology Acceptance Model (TAM)

TAM identifies perceived usefulness (PU) and perceived ease of use (PEOU) as primary drivers of technology acceptance (Davis, 1989). In healthcare studies PU and PEOU reliably predict intention to use telemedicine, EHRs, and mobile apps; PEOU often influences intention indirectly through PU (Taherdoost, 2018). TAM's strength is parsimony and predictive power, but it under-represents affective and personality factors (e.g., trust, technology anxiety) important for patient adoption.

3. Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2)

UTAUT consolidates prior models into core predictors performance expectancy, effort expectancy, social influence, and facilitating conditions with moderators such as age and experience (Venkatesh et al., 2003). UTAUT2 adds consumer factors (hedonic motivation, price value, habit) for broader contexts (Venkatesh et al., 2012). UTAUT is valuable for highlighting environmental and social enablers, though empirical results for social influence vary across settings; it also tends to downplay dispositional readiness and affective concerns.

4. Protection Motivation Theory (PMT)

PMT explains protective behavior via threat appraisal (severity, vulnerability) and coping appraisal (response efficacy, self-efficacy, response cost) (Rogers, 1975). PMT helps explain adoption driven by perceived health threats or prevention motives (e.g., symptom tracking, pandemic apps). It complements acceptance models by addressing motivational and emotional drivers but does not address usability or dispositional readiness on its own.

5. Technology Readiness and Acceptance Model (TRAM)

TRAM integrates Technology Readiness optimism, innovativeness, discomfort, insecurity with TAM's PU and PEOU, linking dispositional traits to system appraisals and intention (Lin et al., 2007; Parasuraman & Colby, 2015). Empirical work shows TRAM often accounts for more variance than TAM alone because it captures both enablers (optimism, innovativeness) and inhibitors (discomfort, insecurity) that shape perceived usefulness, ease of use, and trust in health contexts (Beldad & Hegner, 2017).

6. Rationale for selecting TRAM for this study

TRAM is chosen here because it combines dispositional readiness with perceptual appraisals, a fit for healthcare adoption where trust, privacy concerns, and emotional comfort frequently determine whether perceived benefits lead to use. TRAM also supports testing moderators (e.g., age) shown to alter how readiness and perceptions convert into intention and behavior. For these reasons, TRAM serves as the primary theoretical lens for this study, supplemented by TPB, UTAUT, and PMT constructs where social influence, facilitating conditions, or threat-driven motivations are relevant.

Psychological Factors Influencing M-Health Adoption

This study treats psychological factors as proximal determinants of patients' intention to adopt M-Health apps in KSA. Five interrelated constructs are specified: perceived value, perceived usefulness, perceived ease of use, trust, and health literacy. Each is defined and linked to adoption logic below.

1. Perceived value (PV) is the user's overall judgment of an offering's net benefit what is received (convenience, better outcomes) versus what is given (time, effort, privacy risk) (Zeithaml, 1988). PV is multidimensional (utilitarian, hedonic, social) and in M-Health captures convenience, perceived health benefit, and the social or status gains from using an app (McDougall & Levesque, 2000; Sweeney & Soutar, 2001). Empirical work shows PV strengthens the link between intention and actual use, so PV is modeled here as a key antecedent to behavioral intention and a moderator of intention → use (Yang et al., 2024).

2. Perceived usefulness (PU) and perceived ease of use (PEOU) PU belief that using an app will improve health management and PEOU belief that the app requires little effort derive from TAM and remain core predictors of intention (Davis, 1989). In M-Health, PU reflects expectations of improved monitoring, faster access, and better outcomes; PEOU covers interface clarity, learnability, and low cognitive load. PU typically has the stronger direct effect on intention, while PEOU also influences intention indirectly through PU (Joo & Ha, 2024; Park & Yoon, 2025). Given variation in digital competence in KSA, PEOU is modeled both as an antecedent to PU and as a construct whose effects are moderated by health literacy.

3. Trust denotes willingness to be vulnerable to a provider or system based on expected competence, integrity, and benevolence (Mayer et al., 1995). In M-Health trust includes technical (security), institutional (regulation, provider reputation), and interpersonal (clinician competence) dimensions (Hamdan et al., 2021; Jian et al., 2020). Trust reduces perceived risk and amplifies perceived value and PU; low trust can negate high PU and block adoption (Cao et al., 2024; Liu et al., 2024). In KSA, institutional and cultural trust cues (government endorsement, regulatory transparency) are especially important for converting perceptions into intention (Al-Haddad et al., 2023).

4. Health literacy is the ability to obtain, process, and use health information to make decisions (Berkman et al., 2010); e-health literacy extends that ability to digital sources (Norman & Skinner, 2006). Higher health/e-health literacy raises users' self-efficacy, reduces cognitive load, and increases both PEOU and PU, supporting adoption and sustained use (Emerson et al., 2022; Mahajan et al., 2025). Digital-health literacy varies with age, education, and information-seeking behavior and thus moderates' usability effects (Zhao et al., 2024).

Interaction and Role in the Model

PV aggregates benefit–cost evaluations; PU and PEOU capture utility and usability; trust mitigates perceived risk; and health literacy conditions how users interpret and act on app information. In the conceptual model these psychological constructs operate as direct antecedents of behavioral intention, with health literacy also moderating PEOU → PU and PEOU → intention paths. Measuring trust as technical, institutional, and interpersonal enables capturing KSA-specific nuances that influence whether favorable app perceptions translate into real use.

Technological Readiness

Technological readiness (TR) describes individuals' predisposition to adopt new technologies and is measured by four dimensions: optimism, innovativeness, discomfort, and insecurity (Parasuraman, 2000; Parasuraman & Colby, 2015). TR reflects attitudes rather than technical skill and influences how people judge a system's usefulness and ease of use, thereby shaping adoption indirectly (Lin et al., 2007).

- 1. Optimism** is the belief that technology improves efficiency, control, and quality of life. Optimistic users are more likely to see M-Health apps as useful and to try them; in KSA, national digital initiatives can reinforce optimism but should be paired with realistic communication to avoid unmet expectations (Clausing & Holmes, 2015; Parasuraman & Colby, 2015).
- 2. Innovativeness** is the tendency to try new technologies early. Innovative users adopt sooner and help spread new services. In Saudi settings, innovativeness is higher among younger, urban, and more educated groups, so outreach is needed to raise readiness in other segments (Agarwal & Prasad, 1998; Kim & Kyung, 2023).
- 3. Discomfort** reflects anxiety or a perceived lack of control when using technology. It increases cognitive load and reduces perceived ease of use, but can be reduced by simpler interfaces, language localization, onboarding, and user support (Dash & Mohanty, 2023; Parasuraman & Colby, 2015).
- 4. Insecurity** denotes doubts about reliability, privacy, and data safety. High insecurity undermines trust and lowers adoption intent. For M-Health where sensitive health data are handled clear privacy policies, visible security measures, and institutional

endorsement (e.g., SDAIA/NPHIES) are essential to build confidence (O'Hern & St. Louis, 2023; Parasuraman & Colby, 2015; Sunyaev et al., 2015).

Implications

Combining TR with TAM (the TRAM approach) helps explain which users will adopt M-Health and why. Policy and design actions include promoting realistic success stories to build optimism, engaging early adopters to leverage innovativeness, simplifying UX and providing training to reduce discomfort, and publishing clear data-governance and security measures to lower insecurity and build trust (Lin et al., 2007; Parasuraman & Colby, 2015).

Health consciousness (HC) an individual's cognitive and affective awareness of personal health and the extent to which health concerns guide daily choices (Hong, 2009; Jayanti & Burns, 1998) functions as a key behavioral antecedent in the TRAM-based model of M-Health adoption. Originally framed as willingness to perform health actions or a wellness-oriented lifestyle (Becker et al., 1977; Kraft & Goodell, 1993), HC is now treated as a stable disposition that increases health information seeking, risk appraisal, and preventive behavior (Meng et al., 2019). Highly health-conscious users are more likely to seek, interpret, and act on digital health information and to view M-Health apps as convenient, empowering tools for self-management; empirical studies link HC to higher perceived usefulness, perceived value, and satisfaction with M-Health, which in turn strengthen behavioral intention and continued use (Cao et al., 2024; Meng et al., 2019; Wang & Qi, 2021). In the Saudi context where Vision 2030 and platforms such as Sehhaty have raised public health awareness for parts of the population HC can help convert external prompts (social influence, public campaigns) into internal motivation to adopt digital services, though disparities in digital-health literacy and access (especially among older and rural groups) mean HC's effects should be tested as both a direct predictor and a moderator of readiness → intention pathways (Alharthi, 2025).

Age has been consistently identified as an important factor in the adoption of digital health technologies because it reflects differences in technological experience, cognitive processing, health priorities, and perceptions of risk, all of which shape how individuals evaluate and use M-Health apps (Chiu et al., 2025; Reuter et al., 2010). Empirical evidence suggests that younger users generally demonstrate higher levels of digital fluency, optimism, and innovativeness, which strengthens perceptions of usefulness and ease of use and, in turn, increases adoption intention, whereas older adults are more likely to experience discomfort and insecurity and place greater emphasis on trust, reliability, and simplicity when deciding whether to use M-Health services (Guo et al., 2016; Schomakers et al., 2022; Shemesh & Barnoy, 2020). Importantly, age does not merely exert a direct influence but also moderates key technology acceptance relationships, with prior studies showing that the effects of perceived value, habit, and facilitating conditions on behavioural intention vary significantly across age groups (Harnadi et al., 2024; Venkatesh et al., 2012), as do the impacts of personality traits and individual readiness on adoption behavior in health app contexts (Merhi et al., 2020; Nunes et al., 2018). Within integrated frameworks such as the Technology Readiness and Acceptance Model, age shapes how readiness traits translate into cognitive evaluations, with younger users' optimism and innovativeness amplifying positive appraisals and older users' discomfort and insecurity weakening these effects unless strong usability and institutional trust cues are present (Hua et al., 2021; Zhao et al., 2018). In the Saudi Arabian context, these dynamics are particularly salient, as high smartphone penetration among younger populations contrasts with persistent gaps in digital health literacy among older and

rural users, potentially constraining the conversion of intention into actual M-Health use (Aljohani, 2025; van de Werken et al., 2025). Consequently, age warrants consideration as a moderating variable rather than a mere control, as capturing generational heterogeneity is essential for understanding M-Health adoption and for informing the design of inclusive, patient-centered digital health interventions.

Behavioural Intention, Usage, and Moderating Effects

Behavioural intention is the proximal mechanism that converts psychological and technological antecedents into actual M-Health use, yet empirical work has emphasized direct intention–usage links more than the mediating role of intention. Meta-analyses and primary studies indicate that perceived usefulness, perceived value, trust, and technological readiness predict behavioural intention, which in turn predicts uptake and engagement (Davis, 1989; Free et al., 2013; Parasuraman & Colby, 2015). However, relatively few studies explicitly test behavioural intention as a mediator, limiting understanding of how antecedents (e.g., trust, health literacy, optimism) operate through intention to produce sustained adoption rather than one-off downloads (Norman & Skinner, 2006; Sunyaev et al., 2015).

Demographic moderators especially age significantly shape the conversion of intention into actual use. Older adults frequently report greater usability difficulties, lower e-health literacy, and higher privacy/security concerns, which can attenuate the intention → usage pathway unless facilitating conditions and trust cues are provided (Venkatesh et al., 2012; Berkman et al., 2011). Despite this, age is often included only as a control variable rather than systematically tested as a moderator, leaving gaps in our knowledge of generational differences and the tailored interventions needed to ensure that behavioural intention translates into continued, equitable M-Health adoption.

Motivation and Contribution

Motivated by Saudi Arabia’s Vision 2030 push for digital health, this study fills an important gap by examining mHealth adoption in public hospitals, where individual choices interact with institutional arrangements. Unlike prior work that relies on single acceptance models or focuses on private and Western settings, this research combines psychological, technology-readiness, and behavioral factors in one framework to offer a richer explanation of adoption. Using data from a large patient sample, it provides empirical evidence that behavioral intention is the key mechanism linking antecedent factors to actual use. The findings offer practical guidance for policymakers and hospital managers on designing mHealth programs that match patients’ perceptions, readiness, and health motivations, supporting sustainable digital-health uptake in public systems.

Research Gaps and Future Research Directions

This review highlights three prominent empirical and theoretical gaps. First, few studies integrate psychological constructs (e.g., perceived value, trust, health literacy), dispositional technology-readiness traits (optimism, innovativeness, discomfort, insecurity), and behavioral drivers (health consciousness, protection motives) within a single, testable framework. Existing work is often fragmented across TAM, UTAUT, PMT, or TRI/TRAM approaches, limiting understanding of how dispositional, cognitive, and motivational factors interact to shape adoption (Davis, 1989; Parasuraman & Colby, 2015; Venkatesh et al., 2003). Second, mediation and moderation mechanisms remain under-examined: behavioural

intention is frequently treated as an outcome rather than explicitly tested as a mediator linking antecedents to sustained usage, and age (and other demographics) is often used as a control rather than rigorously evaluated as a moderator of key paths (Norman & Skinner, 2006; Venkatesh et al., 2012). Third, the geographic and sectoral coverage of empirical evidence is uneven most rigorous quantitative studies originate from high-income settings, while public healthcare systems in developing and Middle Eastern contexts (including KSA) are under-represented despite distinct cultural, regulatory, and infrastructural conditions that shape trust, literacy, and facilitating conditions (Berkman et al., 2010; Free et al., 2013; Sunyaev et al., 2015).

To address these gaps, future research should: (a) adopt integrated theoretical frameworks (e.g., TRAM enriched with PMT and value/health-literacy constructs) to model dispositional → perceptual → motivational → behavioral pathways; (b) employ robust causal methods PLS-SEM or covariance-based SEM for theory testing, mediation analysis (bootstrap CIs) for indirect effects, and multi-group or moderated-mediation techniques to evaluate age, gender, and rural/urban heterogeneity; and (c) expand empirical work into under-studied contexts (public hospitals, rural populations, GCC countries) using representative samples. Longitudinal and mixed-methods designs are particularly valuable: cohort or panel studies can distinguish initial adoption from continuance and habituation, while qualitative work can unpack cultural meanings of trust, privacy, and perceived value that shape appraisals and design preferences (Sunyaev et al., 2015). Finally, intervention-focused and translational research is needed to move beyond explanation toward solutions: randomized or quasi-experimental evaluations of usability redesigns, privacy-transparency cues, digital-health literacy programs, and facilitator/support interventions (e.g., family/caregiver onboarding, clinician endorsement) will test causal strategies to increase equitable, sustained M-Health uptake. Policymakers and developers should partner with researchers to implement pragmatic trials embedded in national platforms, generating evidence that is both contextually valid and actionable for health system transformation (Parasuraman & Colby, 2015; Venkatesh et al., 2012)

Conclusion

This review synthesizes evidence showing that patients' adoption of M-Health apps arises from an interdependent set of psychological perceptions (perceived usefulness, perceived ease of use, perceived value, trust, health literacy), dispositional technology readiness (optimism, innovativeness, discomfort, insecurity), and behavioral motivations (health consciousness, protection motives). Integrating TRAM with TAM and complementary models (e.g., PMT, UTAUT) provides a comprehensive lens for explaining how these antecedents shape behavioral intention and translate into usage (Davis, 1989; Parasuraman & Colby, 2015; Venkatesh et al., 2003). Empirical and contextual evidence including KSA's rapid digital health rollout underscore the centrality of trust, usability, and literacy in converting infrastructure into sustained, equitable adoption (Berkman et al., 2010; Free et al., 2013; Sunyaev et al., 2015). Addressing the identified gaps (integrated models, mediation/moderation testing, longitudinal and context-specific studies, and intervention trials) will strengthen theory and guide practical, patient-centered designs and policies that foster long-term engagement with M-Health solutions.

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