Exploring the Future Research Agenda for Health Applications Adoption: A Systematic Literature Review

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***Abstract*—The healthcare sector is experiencing rapid digital transformation, marked by the growing popularity of mobile health (mHealth) and eHealth applications for various health-related purposes. However, despite their potential, the adoption of health applications remains inconsistent due to varying influencing factors. Previous reviews often focused on specific populations or limited frameworks, leaving a gap for a comprehensive synthesis. This study aims to systematically review and consolidate the current understanding of the factors affecting user adoption behavior in health applications. Following the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) guidelines, a comprehensive literature search was conducted to identify relevant studies between 2016 and 2025. A total of 79 primary studies were analyzed to explore the theoretical model, variables, and emerging trends in health applications. The Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) models are the most widely used models by researchers. Beyond these core frameworks, researchers have proposed extended constructs such as psychological factors, health literacy, regulator readiness, security concerns, and infrastructure limitations. This review highlights the need for more inclusive, cross-cultural, and mixed-method research, particularly focusing on underrepresented populations such as rural users, the elderly, and low-literacy groups. These findings offer valuable insight to inform the design of future models and support the development of more effective, context-aware, and user-centered health technologies.**

***Keywords*—Systematic literature review; health application adoption; health technology; user behavior; technology acceptance; TAM; UTAUT**

I. Introduction

In the digital era, internet usage has grown significantly, supported by the rapid advancement of information and communication technology (ICT), including in the healthcare sector. The development of increasingly sophisticated and innovative digital health applications has become a preferred choice for the community because it offers facilities and services that are useful in everyday life. Digital health applications are designed to enhance health awareness, promote healthy lifestyles, lifestyle management, provide access to medical services, monitor medical conditions, interaction between doctors, health professionals and patients. In general, Digital health applications offer customers digital health information services through mobile applications such as Android and iOS or web-based applications. According to the World Health Organization (WHO), eHealth refers to the effective and secure utilization of information technology within the healthcare industry, encompassing domains such as healthcare services, disease monitoring, health-related literature, education, research, and knowledge dissemination [1].

Although health applications have the potential and help improve people's health, their use still faces numerous challenges [2]. People, especially in developing countries, still do not intend to use or tend to rarely use health applications. This raises the question of which factors influence sustained use of health applications. Prior studies on mobile health (mHealth), such as the study by Jacob et al. (2022) [3], have investigated socio-technical factors influencing adoption, including technical barriers, health literacy, social influence, and highlighted challenges such as patient resistance and ethical concerns. However, while their study focused specifically on patient perspectives, this review emphasizes broader technology adoption models—such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT)—to identify behavioral, social, technical, and security-related factors that collectively affect adoption. Unlike previous research, this study also considers multiple stakeholders, including users, developers, and policy factors—and focuses on general health applications rather than disease-specific tools, thus offering a more comprehensive view of the adoption ecosystem.

This study aims to systematically review and consolidate the factors influencing health application adoption, identify the most widely applied theoretical models and their extensions, and categorize adoption determinants into eight domains: technical, psychological, security and trust, cognitive/literacy, health attitude, social, regulatory, and economic. By doing so, the study provides a comprehensive evidence base to inform the design of inclusive, context-aware, and user-centered health technologies.

The remainder of this study is organized as follows: Section II outlines related work to establish the relevance and contribution of this study. Section III describes the methodology, including the PRISMA-based SLR process. Section IV presents the results derived from the research questions. Section V discusses the findings, highlights research gaps, and proposes a future research agenda. Finally, Section VI concludes with implications for researchers, developers, and policymakers.

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II. Related Work

Research on health application adoption has been explored through a range of systematic reviews, each addressing specific technologies, context, or user groups. For example, Aljohani and Chandran [4] systematically reviewed 22 studies on mHealth adoption in developing countries, showing the predominance of TAM but focusing narrowly on patient perspectives and offering limited integration of broader socio-cultural or policy-related factors. Similarly, Ghiwaa et al [5] analyzed 21 studies on telemedicine adoption between 2012 and 2023, identifying TAM and UTAUT as the most frequently applied frameworks but restricting the scope telemedicine delivery contexts and overlooking adoption determinants beyond service providers and patients. In another direction, Ikwunne et al. [6] reviewed on mHealth design processes, synthesized 32 studies and proposed a 16-item checklist to enhance user engagement. However, while valuable for guiding design practices, it did not address adoption determinants systematically across theoretical models.

Beyond these works, reviews in other domains have focused on narrower technological contexts. Jacob et al. [3] examined the adoption of mobile health applications in chronic disease management, emphasizing usability, engagement, and security factors, but its disease-specific focus limited generalizability. Likewise, Al-rawashdeh et al. [7] investigated adoption factors for wearable devices, highlighting perceived usefulness, trust, and cost as critical, but did not integrate a cross-framework perspective or broader population groups. Collectively, these prior reviews provide useful but fragmented insights into adoption, as they tend to emphasize specific technologies, health conditions, or populations, and rarely combine multi-stakeholder viewpoints.

In contrast, the present study contributes a broader and more comprehensive synthesis. By systematically analyzing 79 primary studies published between 2016 and 2025, it integrates multiple theoretical models—including TAM, UTAUT, Theory of Planned Behavior (TPB), Information System (IS) Success Model, and others—while categorizing determinants into eight thematic domains (technical, psychological, security and trust, cognitive/literacy, health attitude, social, regulatory, and economic). Furthermore, this study incorporates a multi-stakeholder perspective encompassing users, developers, and policymakers, and pays explicit attention to underrepresented groups such as rural, elderly, and low-literacy populations. This approach not only consolidates existing findings but also highlight emerging post-COVID-19 trends, thereby offering a timely and holistic contribution to the health application adoption literature.

III. Methodology

A systematic approach for reviewing the literature on health application user behavior is chosen. Systematic literature review (SLR) is now the most widely used review method in the field of information systems. Systematic literature review (SLR), commonly known as systematic review, involves the process of locating, assessing, and analyzing all relevant research studies associated with a specific research topic, question, or phenomenon of interest [8]. The purpose of this research is to explore these questions by conducting a comprehensive examination of prior relevant research and integrating it with current theories using a systematic literature review (SLR) approach. As illustrated in Fig. 1, the Kitchenham SLR method consists of three processes: planning, conducting, and reporting [8].

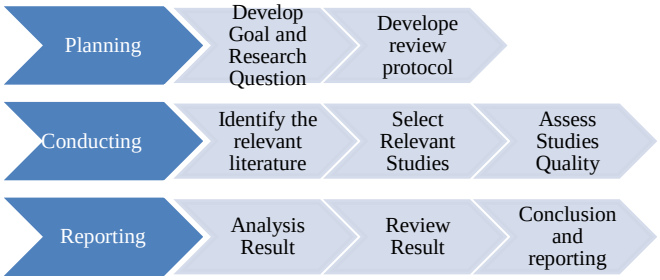

Fig. 1. Systematic Literature Review (SLR) method process.

Undoubtedly, the three key stages of a Systematic Literature Review (SLR) comprise planning, conducting, and reporting the literature review, as depicted in Fig. 1. In the initial phase (Step 1), the requirements for a systematic review are established. In the opening section of this work, the objectives of conducting the literature review were elucidated. Following this, existing systematic reviews on consumer approval of health application activity are identified and evaluated. The purpose of the review process is to provide direction and minimize the likelihood of researcher bias (Step 2). This entails defining the study selection criteria, formulating research questions, determining the search method, assessing quality, and ultimately, extracting and synthesizing data (Step 3).

A. SLR Planning Process

The purpose of specifying the Research Questions (RQ) is to maintain the focus of the review. These questions are formulated using the Population, Intervention, Comparison, Outcomes, and Context (PICOC) criteria, as outlined by Kitchenham and Charters (2007). The structure of the research questions based on the PICOC criteria is presented in Table I.

TABLE I Summary of Picoc

Structure	Scope and Coverage
Population	Digital Health, eHealth, Mobile Health, mHealth, Health Application
Intervention	Model, Method, Acceptance, Readiness, Adoption
Comparison	TAM, UTAUT, The Technology-Organization-Environment (TOE), The Theory of Planned Behavior (TPB), The Health Belief Model (HBM)
Outcome	Successful Adoption, Model Adoption, Technology Behavior
Context	Studies in Health Industry, Software Development, and academia Research

The Research Questions (RQ) and motivation that this literature review addresses are presented in a tabular format as Table II.

TABLE II RESEARCH QUESTIONS ON LITERATURE REVIEW

ID	Research Questions	Motivation
RQ1	Which journal is the most significant publication for user adoption of health applications?	Identify the most significant journal in the model adoption of health application.
RQ2	What kind of theory adoption approach is used most often for user behavior on health applications?	Identify research topics and trends in the model adoption of health applications.
RQ3	What are the factors or constructs that mostly influence user behavior in health application adoption?	Identify the most used factor for model adoption of health applications.

B. SLR Conducting Process

In the process of creating SLR, it is necessary to search and identify all original published articles related to user behavior adoption in health applications. Before beginning the search library, it is vital to choose a set of databases to enhance the finding of highly relevant articles. Science Direct, Springer, Taylor & Francis, IEEE, and Emerald are the most comprehensive lists used for literature search. It is all recorded by the Scopus Database. As displayed in Fig. 2, this review has been conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines [9], [10]. Employing the PRISMA framework demonstrates the progression of information through the various stages of the review [9], [10]. Additionally, it illustrates the quantity of articles that were identified, included, and excluded, along with the rationale for excluding certain articles. The methods used to identify and gather the relevant studies in this review encompassed multiple phases, including defining inclusion and exclusion criteria, determining the sources and digital databases, specifying search strategies, and evaluating the retrieved studies.

The search for pertinent studies was executed using databases that were specifically selected for this objective. In October 2023, a search was carried out to gather research papers published from 2016 to May 2025, covering a ten-year duration. A search strategy was devised using specific keywords that are outlined in Table III. The initial search results yielded a total of 736 studies, as depicted in Fig. 2. The inclusion and exclusion criteria were then applied, and the refinement stages as per the PRISMA were followed. The analysis of the collected studies was performed by the first and third authors of this study, who analyzed each article independently. Any discrepancies in the analysis of the studies between the two authors were resolved through discussion and further review of the disputed studies. As a result, a total of 79 studies were deemed to be valid and were included in the analysis.

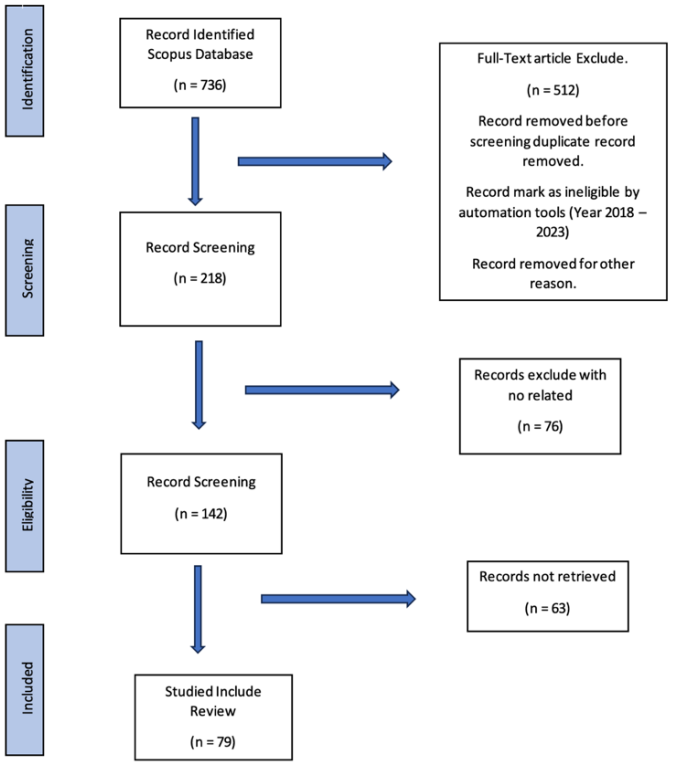

Fig. 2. PRISMA flow diagram.

The inclusion and exclusion criteria are established to determine the selection rules for studies prior to the analysis phase, as indicated in Table III. These criteria are critical for determining the validity of studies to be included in the analysis and ensuring consistency among the reviewed studies.

TABLE III INCLUSION AND EXCLUSION CRITERIA

Criterion	Criterion Dimension
Inclusions	1. Authentic study results were selected only those were published in Scopus journals. 2. Articles that include the terms "Health" and "Model Adoption" in the title, abstract, or keywords. 3. Articles that include the terms "Health" and "Model Acceptance" in the title, abstract, or keywords. 4. Articles that include the terms "Health" and "Model Acceptance" in the title, abstract, or keywords. 5. Article between 2016 and 2025
Exclusions	1. Studies not written in English 2. The paper is recorded in Scopus only in Q1, Q2, Q3, and Q4. 3. The present research focuses on applying technology acceptance or adoption, but not in the context of healthcare (e.g. banking, e-learning, e-commerce). 4. The topic is related to the User perspective. Not Professional healthcare or health worker. 5. The topic focuses on health applications, either mobile or website-based. Not Wearable Device or IoT healthcare.

1) Data collection: The initial phase of the study involved selecting 79 primary studies from 736 publication for analysis. All these studies were thoroughly examined to ensure they met the inclusion and exclusion criteria, as well as to assess their quality, relevance to the research questions, and similarity to one another. Any duplicate studies by the same authors that were published in different journals were removed, leaving a total of 79 primary studies. The complete list of selected studies can be found in the final section of this study. In terms of distribution, Q1 and Q2 dominate the distribution of search results. Data distribution was 47 % Q1, such as Journals from BMC Medical Informatics and Decision Making, Digital Health, Technology in Society, IEEE Access, Journal of Migration and Health, International Journal of Medical Informatics, JMIR mHealth and uHealth, JMIR Public Health and Surveillance, Journal of Biomedical Informatics, etc. Besides, 39 % data distribution was Q2 consist of Journals such as Future Internet, Informatics in Medicine Unlocked, Informatics in Medicine Unlocked, International Journal of Telemedicine and Applications, Healthcare, Health Care for Women International, Transforming Environment: People, Process and Policy, Journal of Computer Information Systems, etc. In contrast, the distribution of Q3 and Q4 data was not as large as the previous data. Q3 contributed 11% which was spread from journals such as TEM Journal, International Journal of Pharmaceutical and Healthcare Marketing, Kybernetes, Journal of Systems and Management Science, and International Journal of Pharmaceutical and Healthcare Marketing. Lastly, 3% was contributed from Q4, where two papers from the journal Asia Pacific Journal of Health Management completed the distribution of publications. Fig. 3 illustrates the distribution quartile of journal articles.

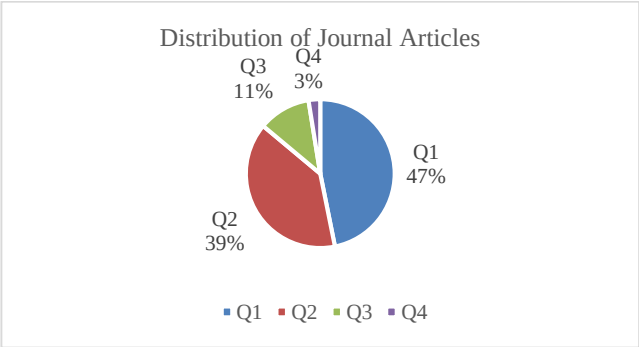

Fig. 3. Quartile distribution of journal articles.

2) Data extraction: The required data to address the research questions outlined in this review were obtained from the selected primary studies. A customized data extraction form was created for each of the 79 chosen primary studies, with a focus on obtaining the necessary information to answer the research questions. These research questions include RQ1: Significant Journal Publications, RQ2: Theory Adoption Approach Used, RQ3: Factors Influencing Adoption.

All collected data adhered to the quality standards set by the study and was utilized to address the research questions. After extraction, the relevant information from each study was compiled into a single Excel file. This file was then used for manual sorting and categorization based on the three research questions. Journals were grouped according to their significant contributions, the theoretical models employed, the factors they identified influencing adoption, any proposed modifications to existing adoption models, and the key challenges and opportunities highlighted in each study. The manual sorting process allowed for a structured approach to analyzing the studies and identifying key patterns and trends.

Additionally, a keyword mapping exercise was conducted using VOS Viewer for the content analysis of research papers related to health app trends, as shown in Fig. 4. The VOS Viewer analysis identified commonly recurring terms such as "Human", "Patient", "Adoption", "Healthcare", and "mHealth". This analysis helped to clarify the broader research focus and trends, complementing the detailed sorting process carried out in Excel. The combination of VOS Viewer for keyword mapping and Excel for manual data sorting enabled a comprehensive understanding of how the research landscape has evolved in health application adoption. The findings from both the Excel sorting and VOS Viewer analysis revealed significant trends related to business models for using health applications, the integration of health applications to monitor health history during the COVID-19 pandemic, and the utilization of decision support systems, artificial intelligence, machine learning, and big data. These findings were sourced from the Scopus database, offering valuable insights for further exploration of health app adoption trends.

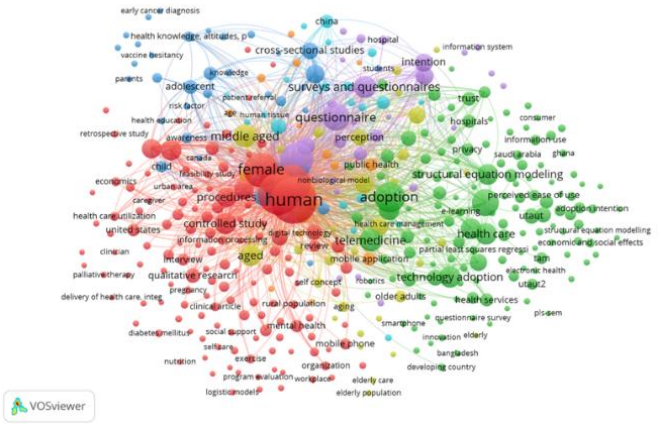

Fig. 4. VOS Viewer's content analysis.

IV. Results

A. RQ1 : The Most Significant Journal Publications

Based on the literature review, 79 primary studies were identified that examined the performance of user behavioral health applications. The data shows a significant increase in research on user behavior in adopting health applications over the past ten years, as evidenced by several published studies, especially since the COVID-19 pandemic in 2020. Fig. 5 depicts research on user behavior and acceptance of health applications. This graph can be used to show that interest in the topic is

increasing year by year. This graph can also be used to show that the topic is a popular topic and interesting to research. The COVID-19 pandemic led to a significant surge in research on the use of health applications from 2019 to 2020. In the subsequent four years, there has been a corresponding increase in studies related to the adoption of health application, aligning with the heightened public consciousness of health issues.

The following Table IV displays the most significant user behaviors in health app acceptance journals, as demonstrated in primary studies that were selected for this purpose. Additionally, Table IV shows the most significant reader behaviors in health application journals, along with their Scimago Journal Rank (SJR) scores and Q categories. The ranking of journal articles is based on their SJR values, which are listed in the table in descending order.

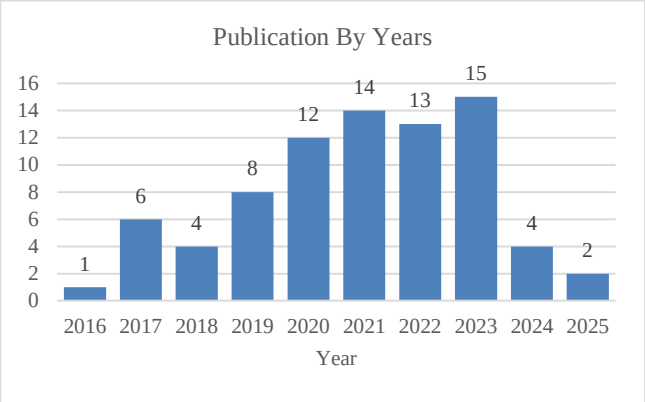

Fig. 5. Article distribution by years from selected papers.

TABLE IV THE MOST SIGNIFICANT DISTRIBUTION SCIMAGO JOURNAL RANK (SJR) OF SELECTED JOURNALS

No	Journal Name	Publisher	SJR	Q in Category
1	International Journal of Information Management journal	Elsevier	4,91	Q1 in Information System
2	Journal of Business Research	Elsevier	2,9	Q1 in Marketing
3	Technological Forecasting and Social Change	Elsevier	2,64	Q1 in Management technology
4	Journal of Medical Internet Research	JMIR Publication	1,99	Q1 in Health Informatics
5	JMIR Public Health and Surveillance	JMIR Publication	1,55	Q1 in Health Informatics
6	JMIR mHealth and uHealth	JMIR Publication	1,51	Q1 in Health Informatics
7	Technology in Society	Elsevier	1,491	Q1 in Business and International Management
8	Journal of Migration and Health	Elsevier	1,45	Q1 in Health (Social Science)
9	Telemedicine Journal and e-Health	Mary Ann Liebert, Inc.	1,24	Q1 in Health Informatics
10	Telemedicine and E-health	Mary Ann Liebert, Inc.	1,237	Q1 in Health Informatics

Table V shows the number of articles published in each journal in the field of information in the health sector. International Journal of Environmental Research and Public Health and Informatics in Medicine Unlocked were the journals most frequently published with four articles each, followed by the journal Technology in Society with three articles, IEEE Access, International Journal of Pharmaceutical and Healthcare Marketing, and Asia Pacific Journal of Health Management with two articles. Table V shows that the field of health application adoption research is active, developing and has increased in the last five years, and there are several journals that are important sources of information for researchers.

TABLE V THE MOST CONTRIBUTED PAPER

No	Journal Name	Quartile	Amount	Source
1	International Journal of Environmental Research and Public Health	Q2	6	[11], [12], [13], [14], [15], [16]
2	Informatics in Medicine Unlocked	Q2	4	[2], [17], [18], [19]
3	International Journal of Medical Informatics	Q1	3	[20], [21], [22]
4	JMIR mHealth and uHealth	Q1	3	[23], [24], [25]
5	Technology in Society	Q1	3	[26], [27], [28]
6	Informatics for Health and Social Care	Q2	3	[29], [30]
7	International Journal of Pharmaceutical and Healthcare Marketing	Q3	3	[31], [32], [33]
8	IEEE Access	Q1	2	[34], [35]
9	International Journal of Pharmaceutical and Healthcare Marketing	Q3	2	[31], [32]
10	Asia Pacific Journal of Health Management	Q4	2	[36], [37]

B. RQ2: The Most Theoretical Approach used

The presented bar chart in Fig. 6 exhibits the distribution of models utilized in the development of health and fitness applications. It is evident that the UTAUT (Unified Theory of Acceptance and Use of Technology) & Extend model holds the predominant position, with 32 findings derived from all applications employing this model. The TAM & Extend model ranks second, with 31 findings originating from all applications utilizing this model. The Information System (IS) Success Model ranks third, appearing in four studies, indicating a moderate but meaningful influence, particularly in contexts where system quality, information quality, and user satisfaction are being evaluated. The Technology Readiness Model was applied in three studies, suggesting an emerging interest in assessing users' predisposition toward new technologies. Models such as the Theory of Planned Behavior (TPB) and Social Cognitive Theory (SCT) were each used in two studies,

often to explore behavior intentions and the influence of perceived control or self-efficacy. Meanwhile, less frequently used model—including the Organizational Support Theory, Diffusion of Innovation Theory (DOI), Technology-Organizational-Environment (TOE) Framework, Health Belief Model, and Interview each appeared in only one study. These limited occurrences suggest that while they may offer unique perspectives, they are not yet widely adopted in the health application domain.

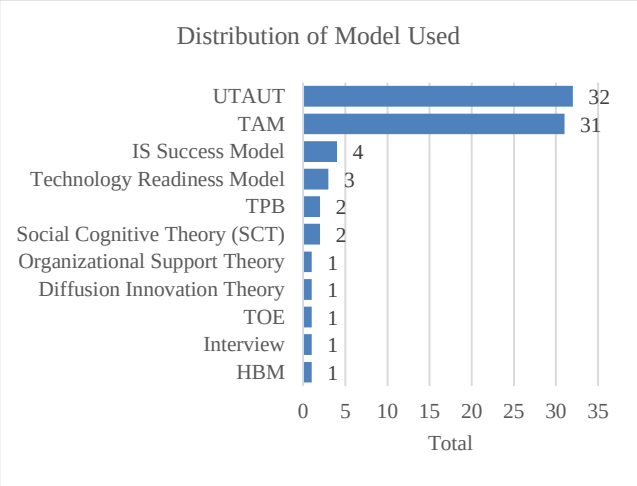

Fig. 6. Distribution of the model used to analyse user behavior in health application adoption.

C. RQ3: The Most Factor or Construct that Influence User

The adoption of health application products and services by users can be influenced by various factors. Identifying and understanding these factors, as well as their impact on the acceptance of health applications, is crucial for researchers in formulating strategies to promote the adoption of health applications and encourage positive user behavior. The classification chart offers a comprehensive summary of non-core variables influencing user adoption of health applications, grouped into eight thematic categories: technical, security and trust, cognitive/literacy, innovativeness, psychological, health attitude, social, regulatory and economic. These factors go beyond core constructs of models like TAM, UTAUT, TPB, or IS Success Model and allow for a deeper understanding of the behavioral, contextual, and environmental elements affecting adoption as illustrated in Fig. 7.

The technical category, which comprises 22.1% of all variables, includes aspects such as compatibility [21], [38], [39], [40], [41], [42], application quality [43], and technology accuracy [42]. These features are essential to ensuring that user experience reliable and responsive systems, which in turn support continued use and engagement. Psychological factors contribute 20.6% of the variables and include constructs such as technology anxiety [11], [22], [26], [28], [44], [45], [46], [47], [48], fatigue [49], perceived enjoyment [32], [37], [50], [51], and intolerance of uncertainty [49]. These variables highlight the emotional and cognitive processes that shape user confidence, resistance, or willingness to adopt digital health platforms. The security and trust category (8.8%) contains variables such as perceived privacy [11], [14], [16], [20], [23], [25], [27], [28], [29], [32], [42], [43], [52], [53], [54], [55], trust [12], [17], [20], [23], [25], [26], [27], [28], [29], [31], [32], [36], [39], [47], [53], [55], [56], [57], [58] , and perceived risk [12], [25], [26], [28], [47], [55], [56], [58], [59]. These elements indicate that without a strong foundation of user trust –especially concerning data protection—adoption is likely to falter, regardless of system quality.

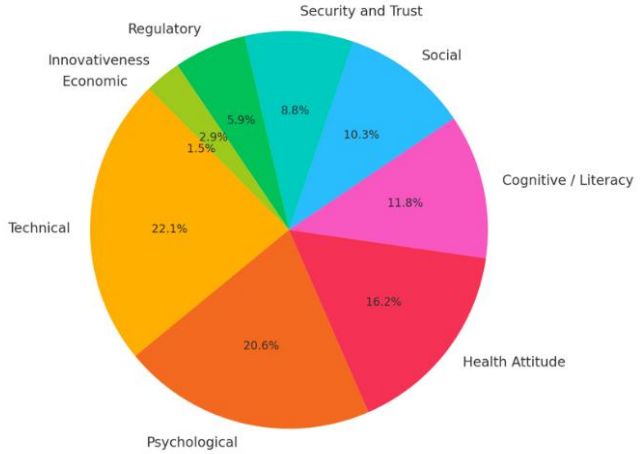

Fig. 7. Distribution of most factors or variables that influence users in health acceptance.

In the cognitive/literacy category (11.8%), factors such as health literacy, IT literacy, and awareness reflect the role of user knowledge in facilitating or hindering adoption. Individuals with a limited understanding of technology or health content may require additional support to engage with applications effectively. Health attitude factors make up 16.2% encompassing health consciousness [12], [36], [42], [60], [61], [62], disease threat perception [43], [47], and personal health status [63]. These beliefs directly influence health behavior, particularly when users perceive a high level of personal risk or benefit. Social factors account for 10.3% of variables and include community support [15], word of mouth [58], and social values [15]. This category emphasizes the role of social environments and peer influence in encouraging technology use, especially in tightly knit or communal populations. The regulatory category (5.9%) includes management support [21], legal concern [25], and user involvement in application implementation [21]. These institutional-level factors highlight that, beyond individual behavior, organizational readiness and policy alignment are key to scaling adoption. Finally, economic considerations account for 1.5% of variables, with affordability [17], [64] being particularly relevant in developing country contexts. The cost burden can be a critical barrier, especially when users perceive that value as insufficient compared to expenses.

V. Analysis, Discussions, And Future Research Agenda

A. Analysis of Users' Acceptance and Behavior in Health Application

The literature collected in this review reveals significant developments and future potential in health adoption research. In recent years, the volume of studies exploring adoption from

users, business, and developer perspectives has increased substantially, reflecting growing interest in understanding the multidimensional dynamics of digital health implementation. Analyzing the VOSviewer data in Fig. 8 illustrates the quantitative data from the collected research literature. Fig. 8 displays a dense and interconnected network of keywords, where each node represents a recurring theme or topic within the literature, and the links illustrate co-occurrence relationships. Based on the analysis, it shows that there is still a growing awareness and potential for research in the topic of health technology adoption, with various factors such as knowledge, attitudes, and behavior of the public. The overlay visualization further incorporates a temporal dimension, with node colors ranging from purple to yellow (indicating 2020 to 2021). The central position of keywords such as "human", "health care", "telemedicine", "mhealth", and "technology acceptance" indicates that these topics have served as conceptual anchors throughout the reviewed period.

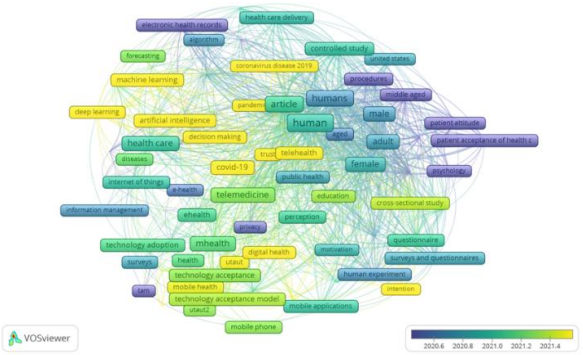

Fig. 8. VOSviewer overlay.

The overlay also shows a noticeable shift in research focus, particularly following the emergence of the COVID-19 pandemic. Keywords such as "covid-19", "telehealth", "machine learning", and "artificial intelligence" appear in brighter hues, reflecting their more recent prominence. This suggests that the global health crisis accelerated the public's awareness of digital health solutions and intensified scholarly interest in the adoption of mobile and AI-enabled health technologies. Accordingly, research on user acceptance of health services has become increasingly prominent, especially as the pandemic exposed both the potential and the urgency of scalable digital interventions. Beyond the influence of COVID-19, the visualization also highlights important sociotechnical factors—such as education, privacy, trust, intention, and perception—that continue to play a critical role in health technology adoption. Social, economic, and demographic factors, including age, gender, and patient attitude, also appear prominently and indicate a growing concern with inclusivity and user diversity. This suggests that future research must be attentive not only to technological readiness, but also to user-specific needs, access inequalities and cultural factors.

Overall, the network shows a research landscape that is theoretically grounded, empirically rich, and methodologically diverse. It offers valuable insights for researchers, health professionals, and policymakers, emphasizing the need to refine behavioral models, integrate intelligence technologies, and design user-centered health applications that are responsive to both global emergencies and long-term public health goals.

On the other hand, this research topic is also on the rise as evidenced by its distribution in several countries. Table VI depicts the distribution of the number of publications based on countries related to the topic of user behavior and health app adoption. The amount indicates that China has the highest number of study cases with 13 publications, followed by Bangladesh and Indonesia with 12 and 8. Saudi Arabia and India are tied with a collection of 6 studies each. According to the data from this study, the topic of user behavior and health app adoption is gaining popularity in developing countries.

TABLE VI DISTRIBUTION OF RESEARCH BY COUNTRY

Name of Country	Amount	References
China	13	[15], [16], [25], [30], [42], [47], [48], [54], [60], [63], [65], [66], [67]
Bangladesh	12	[22], [27], [29], [33], [38], [46], [51], [61], [62], [68], [69], [70]
Indonesia	8	[17], [21], [39], [50], [71], [72], [73], [74]
Saudi Arabia	6	[13], [14], [35], [40], [75], [76]
India	6	[20], [26], [36], [64], [77], [78]
Pakistan	4	[28], [45], [53], [79]
Germany	3	[23], [49], [59]
Portugal	2	[41], [80]
South Korea	2	[11], [37]
Malaysia	2	[81], [82]
Iran	2	[2], [83]
Other countries	19	[12], [18], [24], [31], [32], [34], [43], [44], [52], [56], [57], [58], [84], [85], [86], [87], [88], [89], [90]

B. Discussions and Future Research Agenda

Based on the review of 79 selected manuscripts, several recurring challenges and thematic gaps were identified in the current landscape of health application adoption research. Addressing these gaps is essential to ensure that digital health technologies are inclusive, sustainable, and effective across diverse contexts. One of the persistent issues is demographic bias and inclusivity in health application adoption [12], [14], [20]. Many studies remain focused on younger, urban, well-educated populations with high digital literacy. While these groups represent important early adopters, such a narrow sampling fails to capture the boarder realities of health technology users. Marginalized populations—such as rural communities, older adults, individuals with disabilities and socioeconomically disadvantaged groups—are often underrepresented or excluded altogether. Similarly, generational or gender-based differences are rarely explored in depth. Thus, future research must therefore move beyond convenience sampling toward more purposeful designs, such as stratified sampling or community-based participatory approaches, to ensure the inclusion of underrepresented groups.

Closely related is the challenge of health and IT literacy, which remains as a critical barrier to effective and sustained use of mobile health (mHealth) applications. Users with limited health knowledge, low digital skills, or minimal formal

education often struggle to navigate app functionalities or interpret health information accurately [2], [34], [44]. This issue is particularly acute among groups already facing systemic barriers to healthcare access, such as those from rural area or low-income background. To address this, researchers and developers must prioritize accessible and inclusive principles, including simplified interface, multilingual and voice-assisted instructions, intuitive navigation, and visual cues that require minimal technical knowledge. Complementary efforts, such as community-based digital literacy training, can empower users with limited experience to build confidence and competence in using application health.

Another recurring limitation is the restricted geographical and contextual scope of existing research. Many adoption studies have been conducted within single countries—frequently in urban or institutional settings. This limitation reduces external validity and raises questions about whether theoretical models can be generalized across regions with differing health systems, infrastructure, and cultural norms [14], [26], [27]. Adoption behaviors are not universal but are shaped by contextual realities such as policy framework, economic conditions, and cultural attitudes toward health and technology. To address this, future research should expand into cross-country, and cultural comparative designs. Approaches such as structural equation modelling across diverse populations, meta-analyses, and multinational collaborations could help identify both universal and context-specific determinants of adoption.

The challenge of cost and infrastructure readiness also remains underexplored. Although digital health applications are often promoted as scalable and cost-efficient, the reality of their implementation is often constrained by financial burden and technological limitations [44],[50],[51]. Developing, deploying, and maintaining health applications requires significant investment not only in software, but also in cellular network support, data security protocols, and user support systems. These hidden costs are often not accounted for in studies that focus solely on user-side factors. Addressing these issues requires a strategic plan. First, researchers and developers should prioritize the creation of lightweight, device-independent, offline-capable applications optimized for low-bandwidth environments, while policymakers should integrate digital health into national healthcare plans ensuring alignment with existing systems and long-term financial planning. Public-private partnerships, government subsidies, and donor-funded initiatives may also play a key role in supporting infrastructure, especially in rural area.

The issue of security and privacy remains a critical deterrent to adoption [64], [71], [73]. Although technical safeguard such as encryption and authentication have improved, user perception of trust, transparency, and control are equally influential in shaping behavior. Many applications lack clear consent mechanisms, easy-to-use privacy settings, or transparent data-sharing policies. Inconsistent adherence to international standards amplifies hesitancy, especially in countries with weak regulatory oversight. Future studies should not only advance technical solutions through privacy-by-design approaches but also investigate behavioral and social determinants of trust. Educating users, simplifying privacy tools, and aligning with robust regulatory frameworks are crucial for building confidence in health applications.

Policy and government support also emerged as a foundational yet underdeveloped factor. Despite the growing interest in digital health, many countries lack coherent digital health strategies, legal frameworks, and institutional coordination to support health application adoption [64], [65], [70]. Without government endorsement or integration into formal health systems, health applications often remain fragmented, underfunded, and poorly interoperable. This leads to poor interoperability, weak sustainability, and low public trust. Moving forward, the government must invest in digital health infrastructure by developing clear standards for certification, interoperability, ethical guidelines, and long-term integration into healthcare delivery. The establishment of innovation hubs, public-private collaborations, and participatory policymaking processes can further bridge the gap between national strategies and grassroots health needs.

Another challenge concerns the overreliance on generalized adoption models, such as TAM and UTAUT, which are often applied across various types of health without adjustment for domain-specific needs [23], [39], [60], [66]. While these models provide valuable general insight, they do not sufficiently capture the unique behavioral, clinical, and contextual factors tied to areas such as maternal health, mental health, chronic disease management, or elderly care. Future research must prioritize the development of domain-specific adoption frameworks that incorporate relevant health constructs such as perceived disease threat, mental health or stigma. These tailored models would enhance both theoretical precision and practical relevance.

Methodological gaps also persist, with research dominated by quantitative approaches such as surveys and structural equation modeling [14], [27], [52], [53], [54], [65]. While these methods offer statistical rigor and generalizability, they often fail to capture lived experiences, cultural nuances, and emotional responses that shape real-world adoption. Qualitative methods such as ethnography, longitudinal case studies, or diary methods remain underutilized but could provide critical depth. Mixed-methods research that combines quantitative generalizability with qualitative richness would deliver a more holistic understanding of health application adoption.

In addition, cultural and socio-economic factors remain underexplored. Health applications are embedded within broader social contexts shaped by traditions, norms, and inequalities. Income level, job security, basic smartphone access or even mobile data directly affect adoption capacity, yet these factors are often overlooked in existing models. Future research should adopt culturally responsive and socio-economically inclusive approaches, engaging community-based in the design and testing process to ensure solutions are globally adoptable yet locally relevant.

Finally, psychological factors remain one of the most underexplored dimensions but most influential areas in digital health adoption [20], [26], [69], [72]. Elements such as health motivation, perceived vulnerability, technology-related anxiety, trust, and emotion play a significant role in whether users are willing to initiate and maintain use of health applications, particularly in sensitive health domains such as maternal care or

mental health. Yet these psychological dimensions are rarely integrated into mainstream models. Interdisciplinary collaboration with behavioral psychology and health science can enrich adoption frameworks by incorporating validated psychological constructs, thus yielding more human-centered and emotionally appropriate digital health solutions.

In summary, this review underscores key gaps in health application adoption research, including demographic bias, limited cross-context validation, and the underrepresentation of psychological, cultural, and infrastructural factors. While existing models offer strong foundations, future studies must adopt more inclusive, contextual, and interdisciplinary approaches to ensure broader relevance and impact. Complete references for each challenge and research priority are listed in Table VII.

TABLE VII CHALLENGES AND OPPORTUNITIES

Challenge	Research Gap Identified	Suggested Direction	References
Demographic bias	Most health application users are young / urban users.	Exploring rural, elderly, disabled population, or specific user segmentation (e.g., Gen Z, Gen Y, and female or male) could be considered for future research.	[12], [14], [18], [20], [26], [27], [30], [32], [34], [35], [36], [37], [38], [41], [45], [46], [51], [54], [59], [60], [62], [64], [66], [68], [70], [72], [73], [80], [85], [91]
Health & IT Literation	The user's difficulty in using m-health devices due to low health literacy or education suggests that they are not prepared to utilize m-health applications.	Design user education and support features. In order for the application to continue to be used, issues related to design and ease of use must be prioritized.	[2], [34], [44], [65], [71]
Area / cross-sectional or country	Current research model lacks cross-country validation, limiting the model's generalizability or small sampling area.	The research model used should be tested in different populations in other countries or a wide area.	[14], [20], [26], [27], [32], [38], [41], [51], [52], [53], [61], [62], [64], [77], [84]
Cost and infrastructure technology	The consideration of health applications requires a significant amount of operational development, maintenance costs, and low technology access.	Evaluate cost-efficiency, align with infrastructure readiness	[2], [44], [50], [51], [65], [70]
Security	Despite the increasing use of health applications, limited research has examined the role of security	Ensuring the security of health information systems is crucial in influencing user adoption and continued use	[34], [62], [71], [73]
Policy and government	Lack of policy integration	The aim of this study is to identify the elements within the policy readiness and regulatory dimension that may impact the successful implementation of m-health initiatives.	[2], [17], [34], [50], [64], [65], [70], [75]
Model generalization	Most of the applications evaluated were general health applications.	it is necessary to build more specific applications. (e.g., maternal apps, mental health app, disease prevention apps)	[23], [39], [60], [66]
Mix method	Most existing studies on health applications use quantitative approach.	A mixed method is needed to capture to measurable pattern and rich contextual insight.	[14], [27], [52], [53], [54], [65]
Culture and socio-economic gaps	The factor of socio-culture must be considered in the adoption of healthcare applications, as each location, gender, habit and economic status has a unique culture.	Develop culturally contextualized adoption models.	[23], [27], [28], [36], [39], [46], [61], [66], [68], [70], [74], [85]
Psychologist	Current studies on health application adoption have yet to extensively explore psychological factors	The psychological factors could serve as a potential area of future research in health app adoption studies, as these factors can influence user behavior in using health applications, such as motivation, risk perception, anxiety, and trust.	[20], [26], [69], [72]

VI. CONCLUSION

This literature review investigated trends, theories, and models used in health application adoption research from 2016 to 2025. After applying clear inclusion and exclusion criteria, 79 studies were selected and analyzed. Using the PRISMA framework, this review synthesized empirical findings to answer key research question related to adoption models, influencing factors, and future directions. The Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Acceptance Model (TAM) emerged as the most frequently employed frameworks, cited in over 60 % of the reviewed studies. However, many researchers have extended these core models by integrating contextual and behavioral constructs such as service quality, health consciousness, and personal innovativeness. These enhancements reflect a growing need to

adapt traditional models to complexities of health technology usage in diverse user environments. Despite an increase in scholarly attention over the last decade, several challenges remain. These include the lack of research involving underrepresented populations, limited cross-regional and cross-cultural validation, underutilization of qualitative and mixed-method approaches, and insufficient emphasis on infrastructural, regulator, and psychological aspects. Overall, this research still presents opportunities and challenges that can be explored and studied in the future. As illustrated in Table VII, these include aspects such as the sample respondents, research location, methods employed, more specific applications, government roles and policies, infrastructure supporting the adoption of applications, and public readiness from socioeconomic perspectives.

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