Digital Health Transformation in Saudi Arabia: Examining the Impact of Health Information Seeking on M-Health Adoption during the COVID-19 Pandemic

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ABSTRACT

This study investigates the intention of Saudi Arabian users to adopt mobile health (m-health) applications through the lens of the United Theory of Acceptance and Use of Technology (UTAUT) framework. The research highlights the growing importance of m-health solutions in Saudi Arabia, especially in the context of the country's Vision 2030 development agenda and the accelerated adoption of e-health/m-health technologies during the COVID-19 pandemic. The key findings indicate that health information seeking, and social influence are significant factors driving users' intentions to adopt m-health applications, while Performance Expectancy (PE) is not a primary driver. Additionally, Effort Expectancy (EE) positively influences users' behavioral intentions. Improving health information features in these applications could facilitate broader adoption. This research contributes to the existing literature on information systems and m-health adoption by shedding light on the critical factors influencing user intentions in a developing context. However, the study does not account for all potential technological and external variables that could affect adoption behavior. Future research, particularly qualitative or mixed-method studies, should explore the impact of age on m-health adoption, as the current findings primarily reflect younger users.

Keywords-M-health; apps; factors; adoption; health information seeking; Saudi Arabia

I. INTRODUCTION

In recent years, mobile and wireless technologies have experienced remarkable growth, revolutionizing the delivery of healthcare services. This rapid development has brought an entirely new area of electronic health, known as e-health, which encompasses m-health solutions [1]. While e-health has been associated with desktop applications, m-health shifts the focus to the use of mobile technologies, such as smartphones and tablets, supporting medical and public health practices [2-3]. M-health has gained significant traction, particularly in developing countries, where practical and cost-effective solutions to diverse health challenges are in high demand. This model offers valuable insights for other countries, such as Malaysia, Thailand, and India, where healthcare regulations are being updated to facilitate the adoption of innovative technologies aimed at addressing similar challenges, as observed in [4].

Technological advancements have gradually transformed the healthcare sector in Saudi Arabia, leading to the adoption of computerized information systems. In 2000, the Saudi government launched an e-health strategic plan to establish nationwide frameworks for the digital healthcare [5]. Building on this foundation, Vision 2030 was introduced in 2016 as a comprehensive national development strategy, with its objectives having been outlined by the Ministry of Health (MOH) to enhance workforce capabilities across all sectors and harness the power of technology [6]. With a population of approximately 34 million, with a grow rate of 2.52, the demand for healthcare services continues to rise [7]. Mobile phone ownership in Saudi Arabia increased dramatically, from 11.3 million users, 39.6% of the population, in 2011 to 29.7 million users, 93.5% of the population, in 2017 [8], highlighting the widespread adoption of smartphones among Saudi citizens. Despite this high mobile phone penetration, the adoption of m-health applications by public and private healthcare providers has remained relatively underexplored, as noted in [2].

Traditionally, patients relied on visits to health centers to obtain information about their medical conditions. However, the COVID-19 pandemic significantly accelerated the adoption of e-health and m-health solutions in Saudi Arabia. In response, the government collaborated with private healthcare providers to enhance the existing digital health services and develop new technologies to combat the pandemic. Several notable m-health applications, including Tetamman, Tabaud, Sehhaty, Seha, and Tawakkalna, were launched. These apps played a crucial role in reducing the need for in-person hospital visits, while expanding access to healthcare services across the country [2].

Additionally, the National Mental Health Program (NMHP) partnered with a local counseling app "Labayh," to provide free counseling services, addressing the rising levels of depression and anxiety caused by the pandemic. This demonstrates that seeking health-related information is essential for patients aiming to maintain long-term health [9].

Recent studies, such as [10], reveal a growing trend among cancer patients to use m-health apps for accessing information about their illnesses. Furthermore, the use of m-health apps for doctor consultations and pharmacist interventions has increased significantly. Authors in [11] note that m-health apps focused on weight management have gained popularity in Saudi Arabia, driven by the increasing obesity rates and the ability to monitor health in relation to lifestyle changes. Notably, these apps are particularly popular among young people, who demonstrate higher engagement with digital tools compared to older individuals. Nevertheless, a segment of the population still prefers traditional methods for obtaining health information.

This study aims to identify and validate the factors influencing m-health adoption in Saudi Arabia, with a specific focus on how the health information-seeking behavior affects the app usage. Accordingly, the study addresses the following research question to contribute to this emerging field:

Does the process of health information seeking influence users' behavioral intention to use m-health applications in Saudi Arabia during the COVID-19 pandemic?

II. LITERATURE REVIEW

A. Mobile Health Apps

The rapid advancements in healthcare technologies present significant challenges and opportunities for both developed and developing countries. According to [1], many developing nations aim to implement m-health solutions as a means of providing high-quality healthcare services. For example, the Chinese government launched the "Health China" campaign in 2016 to address the shortage of medical professionals and enhance the country's healthcare infrastructure [12]. Similarly, health technologies have been introduced and implemented in various countries including Malaysia, Thailand, and India, to support healthcare professionals in integrating the emerging technology [2]. As part of its Digital India Program, the Indian government launched several global m-health projects in 2016. These initiatives aimed to improve the access to healthcare, reduce costs, and strengthen healthcare systems [4]. M-health applications manage vast amounts of data, while the effective utilization of health analytics and big data has been proven to significantly improve the health outcomes [13].

B. Mobile Health Apps in Saudi Arabia

Saudi Arabia has demonstrated a strong commitment to integrating e-health and m-health technologies into its healthcare system. The establishment of the National Health Information Centre aims to automate the access to all health records, ensuring efficiency and accessibility. Recognizing the disparity between the rural and urban areas in healthcare accessibility, the MOH introduced a progressive telemedicine policy to bridge this gap.

Prior to the COVID-19 pandemic, the MOH launched initiatives, such as 'Sehhaty' (My Health), which promotes healthy lifestyle activities, and 'Mawid' (Appointment), which encourages citizens to book medical appointments online [9]. The pandemic acted as a catalytic factor, accelerating the adoption and development of e-health and m-health solutions in Saudi Arabia. To curb the spread of the pandemic, the government leveraged existing digital health platforms while collaborating with private healthcare providers to create new technologies.

Several m-health applications were developed and launched, like Tetamman, Tabaud, Sehhaty, Seha, or even Tawakkalna. Most of the hospitals with inactive or emerging digital health applications activated them [9]. One particular hospital initiated the use of a robot to run its intensive care units from a remote location. Riyadh's King Saud Medical City and Dr Sulaiman Al Habib Medical Group implemented their teleconsultation applications, while some relied on WhatsApp for the questions and administrative procedures of the patients' records [2]. This eased the pressure on the burden of physical visits to the hospital as it increased the access to essential healthcare services. Moreover, considering the alarming cases related to sadness and anxiety during the pandemic, more counseling centers needed to be built.

C. Impact of Internet in Saudi Arabia

The role of technology in healthcare has expanded significantly. While it is essential for patients to access reliable health advice through digital platforms, there is also a need for control over the quality of information shared online. The internet has profoundly impacted the way people live, communicate, and access health information [14]. The growing diffusion of the internet has made it easier for consumers to access health-related information, although the quality and accuracy of this information are often poor and sometimes difficult to verify [15].

According to the World Health Organization, many people in developing countries use the internet to search for information on healthy living, joining online communities to discuss problems, and buying goods and services for long-term well-being [16]. However, patients may also encounter inaccurate medical information and advice, posing risks to their health. For this reason, some studies emphasize the need for healthcare providers to be reliable sources of information. Authors in [17], affirm that healthcare professionals must acknowledge the growing trend of patients seeking medical information online. They should also be prepared to guide patients on the reliability of online health resources and the accuracy of the information they find. Additionally, recommendations from health experts have been identified as a powerful determinant of healthy behavior and the adoption of health-related technologies [16-17].

Medical apps should also adhere to legal and safety regulations to avoid the spread of false or harmful information. Regulatory bodies, such as the Food and Drug Administration, have been involved in overseeing these standards. Healthcare professionals are often considered the most trustworthy source of health information by the adult population of the United

States [18]. In Saudi Arabia, internet usage exceeds 64% with an increasing year on year growth [19]. This widespread internet penetration makes it common for Saudi citizens to seek health-related information online. Despite this, there has been limited research into how the process of obtaining health information during the COVID-19 pandemic has influenced the willingness of patients to adopt m-health apps.

D. The Unified Theory of Acceptance and Use of Technology

Authors in [20] indicated that the most widely adopted research framework for understanding the factors influencing the adoption of healthcare innovations is the UTAUT. The UTAUT model was formulated based on an analysis of eight preceding models in the domain of information systems and use behavior. It identifies four key exogenous constructs: PE, social influence, EE, and facilitating circumstances, which influence the endogenous constructs of the behavioral intention to use technology and usage behavior [21]. The model also incorporates four moderating variables: gender, age, voluntariness, and experience. The inclusion of these moderators enhances the model's predictive capability, achieving a 70% accuracy rate in explaining user acceptance and use of technology, compared to the lower predictive rates observed in earlier models, such as the Technology Acceptance Model (TAM) model. In [22], authors applied the UTAUT model to investigate the factors affecting the adoption of the m-health services among elderly consumers in Bangladesh. Their study demonstrated the model's effectiveness in exploring the acceptance of healthcare technology. Numerous other studies have similarly investigated the UTAUT model, confirming its relevance and efficiency in examining the factors that drive the acceptance and use of innovative healthcare solutions. In this research, behavioral intention serves as the primary predictor, offering insights into why patients in Saudi Arabia might accept and adopt m-health applications.

III. CURRENT RESEARCH

Traditional factors associated with the development and adoption of m-health applications are underrepresented in the Saudi Arabian content due to a scarcity of research. This study examines the factors that influence the patients' intentions to adopt m-health apps in Saudi Arabia by incorporating health information seeking as an extended variable within the UTAUT model. The research highlights the growing significance of m-health programs, especially in alignment with the country's Vision 2030 national development agenda. It also explores how the COVID-19 pandemic accelerated the adoption of e-health and m-health solutions, emphasizing their increasing relevance in the healthcare landscape. Many scholars have developed various models and frameworks to estimate the adoption of new technologies and determine the factors that influence consumer behavior. Several studies underscore the intention to use as a key factor for the adoption of m-health services [2, 22-23]. The UTAUT model has become a widely used framework in the healthcare technology research due to its established reliability and validation for studying technology adoption, acceptance, and utilization [20]. However, additional elements tailored to the healthcare environment are necessary. In [16, 18], it is highlighted that the recommendations from healthcare providers are a consistent predictor of future healthy behaviors, underscoring their importance in influencing the m-health adoption.

This research focuses on health information seeking through apps provided by healthcare authorities, which serve as a platform for delivering timely and reliable information to patients. While the behavioral intention to adopt m-health apps has been explored, its role in facilitating the health information seeking remains understudied. This study investigates the impact of health information seeking and the four primary constructs of the UTAUT model on the behavioral intention to adopt m-health apps in Saudi Arabia. Moderators within the UTAUT model are excluded, as this study focuses on early adopters, or existing users, of m-health apps in Saudi Arabia. Given the recent emergence of the m-health in the country's healthcare sector, this research provides valuable insights for the government bodies, healthcare authorities, private providers, and app developers. Understanding the factors driving the m-health app adoption will support the health digitization efforts and improve the access to reliable health information.

IV. THEORETICAL FOUNDATION AND HYPOTHESIS DEVELOPMENT

This research examines the determinants of the intention to use m-health applications in Saudi Arabia, utilizing the core constructs of the UTAUT model. The construct of "facilitating conditions" has been excluded, as it primarily influences usage behavior in the original theory. Similarly, "use behavior" has been omitted from the research model, as the focus is on understanding the factors influencing the m-health app adoption prior to their actual implementation. Additionally, the moderators within the UTAUT model have been omitted. This decision stems from the research's emphasis on the current users of m-health applications in Saudi Arabia.

A. Performance Expectancy

PE is a core construct in the UTAUT model, defined as "the degree to which an individual believes that using the particular system will support him or her in attaining improvements related to job performance" [21]. Several studies indicated a positive relationship between PE and intention to use. In [24], it was highlighted that PE was the most influential determinant of the usage of both fitness and diabetes apps across a sample of over 165 German users, and PE was defined as the "utility of a technology," reflecting the value of technology. Similarly, authors in [22] showed that PE positively relates to the likelihood of the acceptance of the m-health services. Based on the meaning of different terms in [21], and the measurement items in previous articles [1, 22-24], it can be speculated that PE would successfully convey the utility and value of the app. Apps that can effectively meet the expectations of users' needs and provide benefits and preference are likely to be adopted and approved for usage. Thus, the following hypothesis is proposed:

H1: PE positively affects users' behavioral intentions to adopt m-health apps.

B. Effort Expectancy

EE is defined as "the degree of ease associated with the use of the system" [21]. The strong impact of EE has been confirmed by multiple studies [1, 16, 22-25]. According to [22], EE serves as a critical factor in determining users' intentions to adopt m-health monitoring systems, telehealth services, and medical decision support systems. A higher level of ease of use often motivates users to adopt the technology, as authors in [25] suggest, emphasizing the importance of user-friendly designs. Furthermore, in [16], authors argue that the involvement of end users in the design and development processes of m-health systems can significantly enhance the latter's usability and adoption. Based on the foregoing facts, the hypothesis is proposed as:

H2: EE positively affects users' behavioral intentions to adopt m-health apps.

C. Social Influence

Social influence refers to the degree to which an individual perceives that the significant others expect them to adopt and use a new system, as defined in [21]. Several studies have demonstrated the substantial and positive impact of the social influence on individuals' intention to embrace and utilize new technologies, particularly in the healthcare sector [1-2, 22]. Empirical evidence has highlighted that receiving social support is a crucial factor in facilitating behavioral changes [1-2, 16]. For example, analytical findings emphasize the importance of the social effect in predicting the likelihood of adopting and accepting m-health applications [2]. This concept is also well-documented in various theoretical frameworks and models that examine the adoption of health technologies. Authors in [23] in their comparative study on the adoption of Electronic Health Records (EHR) in the United States and Portugal, demonstrated the significance of social influence as a determinant in EHR implementation across both countries. According to previous research, this study posits that social influence has a positive impact on patients' behavioral intentions to use m-health apps. Thus, the subsequent hypothesis is proposed:

H3: Social influence positively affects users' behavioral intentions to adopt m-health apps.

D. Health Information Seeking

Health information seeking refers to the collection of techniques individuals utilize to acquire information about their health, activities to maintain well-being, factors that pose risk, and illnesses [26]. Health information obtained from the Internet impacts consumers' health preferences and choices [27]. Improving the access to healthcare services and strategies for illness management remains a complex challenge [28]. However, empowering individuals through health information has been shown to improve the health outcomes and reduce the hospitalization rates.

During the COVID-19 pandemic, social media played a crucial role in disseminating information about the disease, including updates on the epidemic's progression, news, and containment measures [2]. A study among internet users in Spain revealed that most respondents did not fully trust online information [29]. Concerns about the credibility in online health persist, and the development of standardized criteria for health websites has become a new challenge in public health.

Medical practitioners are regarded as primary custodians of health service provision. Authors in [18] argue that medical apps should adhere to safety laws and standards to minimize the risks associated with inaccurate information. In [14], authors discuss the healthcare providers' role in m-health adoption, highlighting that the key factors influencing the use of digital health technology include patient safety, quality clinical outcomes, and recommendations from other physicians. Their findings suggest that healthcare professionals are more likely to recommend m-health applications to their patients if they believe these tools meet safety and quality standards.

Furthermore, authors in [18] claim that the internet adoption rates have facilitated the use of m-health in dispensing various health-related services. M-health is increasingly viewed as an essential tool for preventing illness, managing diseases, and offering health-related consultations.

This shift is partly attributed to the growing patient awareness of their health, which has generated higher adoption rates of digital technologies in healthcare. For instance, the Ministry of Health in Saudi Arabia leveraged mobile applications during COVID-19 to post health information and recommendations. These included probable symptoms of the disease and advice on prevention [30]. Using credible sources for disseminating health information and advice could drive a greater adoption of the m-health applications. Based on this content, the following hypothesis is proposed:

H4: Health information seeking positively affects users' behavioral intentions to adopt m-health apps.

The above hypotheses were used to develop the research model displayed in Figure 1.

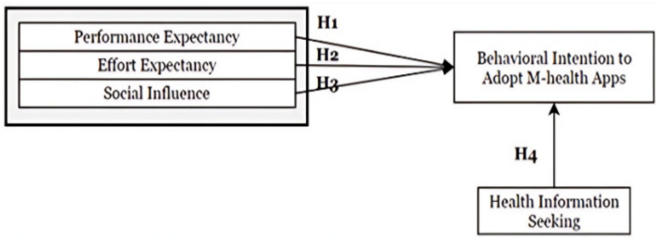

Fig. 1. Research model.

V. REASEARCH METHODOLOGY

This study employs a quantitative approach to gather data from users of Saudi m-health apps. The survey items were developed using previously validated instruments and subjected to pilot testing to ensure reliability and validity. Initially drafted in English, the survey was translated into Arabic to serve to the target demographic. A translation expert reviewed the questions to avoid misunderstandings and inaccuracies in terminology. A pilot test was conducted to enhance the final bilingual version before dissemination to selected researchers and potential users.

The survey employed a five-point Likert scale, ranging from 1 (very strongly disagree) to 5 (strongly agree), to evaluate the responses. The questionnaire was distributed online through social media platforms, including the Twitter and WhatsApp Health groups. Due to the challenges in direct communication with patients during clinic visits, the online survey was the primary method used to achieve the target number of responses. Participation was restricted to individuals meeting the inclusion criteria: responders had to be at least 18 years old and have prior experience using m-health applications. Of the 400 responses received, 343 were deemed valid after excluding incomplete responses and those from individuals below the age threshold.

To evaluate and validate the conceptual model of hypothesis relationships, this study utilizes the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which is a statistical methodology [31]. For the data analysis, the study employed SmartPLS 4, a widely recognized tool among analysts working with PLS-SEM methodologies.

VI. DATA ANALYSIS

A. *Descriptive Analysis*

Table I presents the demographic information reported by the study participants. The descriptive data indicate that 56% of the respondents were males, while 44% were females. Regarding the age distribution, 45% of the participants were aged 25-34, followed by 32% in the 18-24 age group, and 16% aged 35-44. In terms of the educational level, the majority, 51%, held a bachelor's degree, followed by 20% who had completed high school, and 14% with a master's degree.

TABLE I. PARTICIPANT'S DEMOGRAPHICS

Variable	Description	Frequency	Percentage
Gender	Male	192	56%
	Female	151	44%
Age	18-24	110	32%
	25-34	154	45%
	35-44	55	16%
	45-49	21	6%
	60 and above	3	1
Educational level	Less than High School	3	1%
	High school	69	20%
	Diploma	34	10%
	Bachelor	175	51%
	Master	48	14%
	PhD	14	4%

B. *Measurement Model Assessment*

1) *Reliability and Vlidity Assessment*

The first analytical stage involved assessing the internal consistency, convergent validity, and discriminant validity [31]. Authors in [32], emphasize the importance of having multiple items to measure each variable. Factor loadings, which reflect the extent to which each item contributes to the measurement of its respective construct, were examined. According to [33], factor loadings are categorized as: loadings less than 0.3 are considered low, those around 0.5 moderate, and those more than 0.7 high. In this investigation, only high factor loadings were deemed acceptable.

Table II presents the quantitative evaluation of reliability. According to [34], reliability refers to the internal consistency of a measurement scale, which is essential for evaluating whether the scale adequately measures a variable. Common methods used to assess reliability include Cronbach's Alpha (CA) and Composite Reliability (CR) [31]. A CA value of 0.70 or higher is typically used to check for internal consistency. Convergent validity was assessed utilizing the Average Extracted Variance (AVE) and CR [31]. The AVE should be at least 0.50, and the CR should exceed the AVE value.

Another type of validity, discriminant validity, was assessed by comparing the obtained correlation between two latent variables to the square root of the average variance extracted for each construct. According to [31], discriminant validity is established when the square root of the AVE for a construct is greater than its correlations with other constructs. Following the criterion from [35], the diagonal bold values, outlined in Table II, should be greater than the corresponding values in the columns and rows. The results show that all values meet this criterion, confirming the presence of discriminant validity.

TABLE II. RELIABILITY AND VALIDITY ASSESSMENT

	BI	EE	HIS	PE	SI
CA	0.881	0.840	0.859	0.839	0.864
rho_A	0.883	0.846	0.864	0843	0869
CR	0918	0.893	0.905	0.892	0.917
AVE	0.738	0.677	0.703	0.675	0.786
BI	0.859	0.480	0.611	0.436	0.514
EE	-	0.823	0.542	0.579	0.401
HIS	-	-	0.839	0.441	0.536
PE	-	-	-	0.822	0.381
SI	-	-	-	-	0.887

C. *Structural Model Assessment*

1) *Path Testing*

The hypotheses of the study were estimated using Structural Equation Modeling (SEM). The results, including the coefficients and significance values, are presented in Table III. The bootstrapping method was applied to calculate the path coefficient. In SmartPLS 4.0, bootstrapping can be performed for both the inner and outer models, allowing users to specify the t-value for a specific level of statistical significance [31]. For a hypothesis to be accepted, it should support the stated directed hypothesis, with a p-value less than 0.05, and a t-value greater than 1.96. Table II and Figure 2 present the results of the path test.

TABLE III. HYPOTHESIS TESTING

Path	EE→BI	HIS→BI	PE→BI	SI→BI
Original Sample	0.186	0.344	0.091	0.248
Sample Mean	0.184	0.349	0.093	0.248
St. Dev.	0.057	0.052	0.052	0.050
T Statistics	3.269	6.621	1.748	4.971
P Value	0.001	0.000	0.081	0.000
Supported?	Yes	Yes	No	Yes

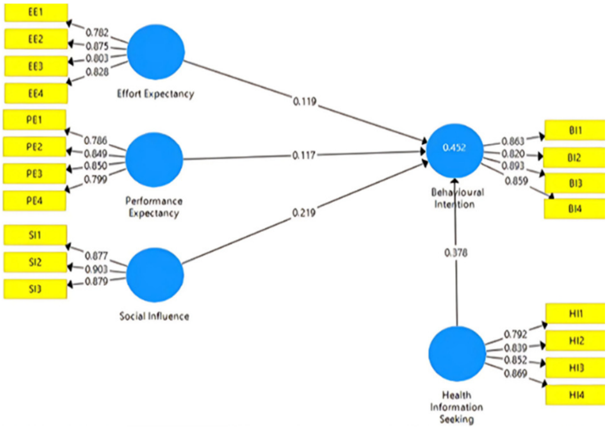

Fig. 2. Path Testing.

2) *Coeffcient of Determination (R^2)*

According to [36], the interpretation of R^2 values is as follows: values above 0.67 are considered strong, between 0.33 and 0.67 moderate, between 0.19 and 0.33 low, while R^2 values below 0.19 are considered undesirable. In this study, the R^2 value for behavioral intention was found to be 0.452 (moderate).

3) *Model Fit*

The appropriateness and fitness of the model are crucial and are usually perceived as a primary goal in factor analysis. SmartPLS provides two important measures of model fitness: Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). According to [37], the SRMR value is considered acceptable if it is less than 0.08. Another important measure for the fitness of a model is NFI, which ranges from 0 to 1. Authors in [38] argue that a threshold value of 0.9 is appropriate. In this study, the NFI value was found to be 0.834, while the SRMR score was 0.072. These results indicate that the model is effective and provides a good fit. Table IV presents the model fit results.

TABLE IV. MODEL FIT RESULTS

	Saturated Model	Estimated Model
SRMR	0.060	0.060
d_ULS	0.674	0.674
d_G	0.309	0.309
Chi_square	643.	643.
NFI	0.834	0.834

VII. DISCUSSION

This study adapts the UTAUT model to explain patients' intentions to adopt m-health applications in Saudi Arabia, aligning with the research objectives. Moreover, the study extends the work of [2], where authors provided valuable insights into the adoption of m-health applications in Saudi Arabia. The factors identified in their study, namely EE, social influence, and healthcare authority enforcement, played a significant role in shaping the behavioral intentions toward the m-health adoption. Although previous studies have looked at the health information seeking behavior in general, the current research narrows its focus to the health information-seeking behavior during the COVID-19 pandemic, offering a timely explanation of user motivations in this critical context. In contrast to the emphasis on the role of regulatory support in improving adoption rates [2], this study focuses specifically on user needs related to the access to health information. This indicates that, for users, the availability of health information was prioritized over the perceived effectiveness, shifting the focus of user experience design toward improving access to information, especially in crisis situations.

Moreover, Table III and Figure 2 illustrate the ranking order of the factors influencing the behavioral intention: health information seeking ranks the highest, followed by social influence, with performance expectation having the weakest relationship with behavioral intention. From Table III, it can be concluded that PE does not significantly influence behavioral intention. This is supported by a p-value of 0.081, which exceeds the threshold of 0.05, along with a t-value below 1.96. As a result, the first hypothesis of the study is rejected. On the other hand, the effect size of EE seeking on behavioral intention is 0.186, with a p-value of 0.001, which is below 0.05, supporting the acceptance of the second hypothesis. Additionally, the study reveals a statistically significant positive effect of the social influence on behavioral intention, accounting for 24.8% of the variance. This is supported by a p-value of less than 0.05 and a t-value of 4.971, confirming the third hypothesis. The findings also show that health information seeking has a 34.4% positive effect on behavioral intention. This result is statistically significant, with a p-value of less than 0.05 and a t-value above 1.96, leading to the acceptance of the fourth hypothesis. These results suggest that the act of seeking health information itself has a greater impact on the m-health adoption than purely technical factors. Therefore, users of Saudi m-health applications are more likely to be positively influenced by their tendency to seek medical information and consultations through these applications.

However, several limitations must be considered in the current study. First, the study exclusively relied on a quantitative approach. Incorporating qualitative or mixed methods would provide deeper insights and more comprehensive data, which could further enrich research on m-health adoption. Second, the research model did not account for all potential variables that could influence an individual's decision to use m-health applications. Finally, the findings are primarily generalizable to younger populations. Even though this reflects the majority of m-health users, it may not be applicable to older age groups. Elderly individuals, who are more vulnerable to illness, could represent another key consumer segment. Future research should therefore assess the applicability of these findings across different age demographics, particularly in the context of developing nations. This would require age-based efforts to explore the adoption factors of m-health apps.

Based on the findings of this study, the following specific and actionable recommendations are proposed to enhance the adoption and usage of m-health applications, especially in crisis situations:

- Improve Access to Health Information: To facilitate effective use of m-health applications, it is crucial to develop user-friendly interfaces that support easy navigation. The design should prioritize simplicity, ensuring that users can quickly find the information they need. Additionally, including resource centers with reliable medical information, Frequently Asked Questions (FAQs), and instructional tutorials will further empower users in their health information-seeking efforts.

- Leverage Social Influence: Engaging trusted community leaders to publicly endorse m-health applications can significantly increase user confidence and encourage wider adoption. By involving influential figures within communities, stakeholders can build trust and foster a sense of community around m-health interventions. Social media campaigns that highlight user testimonials and success stories will create a sense of belonging and raise demand for m-health solutions.
- Targeted User Education: It is essential to educate potential users, especially elderly individuals, about the benefits and functionalities of m-health applications. Workshops and webinars can be organized to help users understand the value of these apps. Additionally, simple educational tools, such as easy-to-understand guides or instructional videos, should be created to assist users in navigating the app and utilizing it effectively for their health information-seeking needs.
- Improve Technical Support: Establishing dedicated help desks for technical support will allow users to quickly address any inquiries or issues they encounter. Additionally, embedding feedback mechanisms within the apps will allow users to share their experiences and suggestions. This input can be invaluable for improving app features and ensuring that the technology meets users' needs and expectations.
- Adapt Applications to Suit Diversified Demographics: m-health applications should be adapted to meet the needs of various demographic groups. For example, elderly users may benefit from features, such as larger text sizes, voice commands, and simplified navigation. Marketing strategies should also be tailored to address the concerns and preferences of age-specific groups. This will help certify that m-health applications resonate with these populations and lead to better user outcomes.
- Collaboration with the Health Authorities: Strong partnerships between the m-health application providers and healthcare authorities are essential for ascertaining that these apps are integrated into standard patient care. Collaborations with healthcare providers can help align the features of m-health apps with public health initiatives, particularly during emergencies or crises. This integration will promote the adoption of preventive health measures and improve public health education in times of crisis

VIII. CONCLUSIONS

The rapid evolution of m-health applications presents a critical opportunity to improve healthcare delivery, particularly in developing countries like Saudi Arabia. Although m-health has gained significant attention in the content of the Saudi Vision 2030 development agenda, factors affecting user adoption remain underexplored. This study addresses this gap by investigating the intention of users in Saudi Arabia towards m-health applications, guided by the UTAUT framework.

The findings revealed that health information seeking, and social factors are the primary drivers of the intention to adopt the m-health application, while Performance Expectancy (PE) was less influential. This suggests that users prioritize the accessibility of information rather over concerns about the technological effectiveness of the applications. Additionally, Effort Expectancy (EE) emerged as a positive factor influencing adoption, highlighting the importance of the intuitive user experience design. These findings shift the focus from the technological functionalities to the motivation behind user engagement with m-health applications. By emphasizing the importance of health information, the study suggests that m-health applications that prioritize user-friendly, easily accessible health resources are more likely to see widespread adoption.

This research extends the existing literature by providing deeper insights into the user intentions in the context of m-health adoption in Saudi Arabia, offering valuable implications for policymakers, health service providers, and developers. To encourage greater adoption, stakeholders should focus on enhancing features that cater to information-seeking behaviors, such as easy navigation and access to credible health data. Furthermore, the study highlights the underrepresentation of older age groups in the adoption of m-health applications. Future research employing qualitative and mixed methods should explore age-related determinants, especially for older adults who may face unique challenges in adopting health technologies.

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