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USE OF MOBILE HEALTH APPLICATIONS BY LAY USERS IN KUWAIT

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ABSTRACT

Aim/Purpose	This study aims to explore the use of mobile health applications (mHealth apps) by lay users in Kuwait. Specifically, it seeks to: (i) identify and highlight the impact of factors that contribute to their use of mHealth apps and (ii) validate a model of these users' usage of mHealth apps.
Background	The advancement of information technologies has paved the way for efficiency and effectiveness in healthcare sectors in developed countries. Kuwait has attempted to revolutionise healthcare systems through mobile applications of information technology solutions to educate users on better methods of receiving customised health services. However, end-user usage of mHealth apps remains in the infancy in developing countries, including Kuwait. Lay users are often vulnerable and frequently overlooked by researchers and health technology providers.
Methodology	A cross-sectional study was conducted among 225 lay users of mHealth apps in Kuwait using an online questionnaire to achieve the study objectives. A purposive sampling method utilising convenience and snowballing sampling techniques was used in which all the respondents were lay users. Descriptive statistics, Pearson correlation, and regression analyses were employed to analyse the collected data.
Contribution	The study contributes to the extant literature on health informatics and mHealth by providing a comprehensive understanding of how technological, social, and functional factors are related to mHealth apps in the context of developing countries. It identifies key drivers of mHealth app use, suggests expanding the TAM model, and facilitates comparisons with developed countries, addressing gaps in mHealth research.

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Findings	Four factors (i.e., perceived trust (PT), perceived ease of use (PEU) and behaviour control (PBC), perceived usefulness (PU), and subjective norms (SN)) were identified that influence the use of mHealth apps. These four identified factors also contributed to lay users' use of these mHealth apps. Among these four factors, perceived trust (PT) was the main contributor to lay users' use of these mHealth apps.
Recommendations for Practitioners	Based on the empirical results, this study provides feasible recommendations for the government, healthcare providers, and developers of mHealth apps. The findings urge developers to enhance app functionality by prioritising privacy and security to build user trust while outlining guidelines for future development focused on user-centric design and compliance with data privacy regulations. Additionally, the government should establish supportive policies and funding, ensure regulatory oversight, and promote public awareness to foster trust. Healthcare providers should integrate mHealth apps into their services, train staff for practical use, gather users' feedback, and collaborate with developers to create tailored healthcare solutions.
Future Research	Additional research is required to apply probability sampling techniques and increase the sample size to generate more reliable and generalisable findings. Additionally, the young age segment must be considered here, and research must be extended to consider the moderating role of demographic factors like age, gender, and educational levels to better understand the adoption of mHealth apps.
Keywords	lay users, health information, mHealth, Kuwait, mobile health applications

INTRODUCTION

Over the past decades, the world has changed at a rapid pace with new emerging technologies. After the rapid advances in information and communication technology (ICT), the demand for the adoption of mobile health (mHealth) paved the way for alternative healthcare delivery systems with improved internet connectivity, particularly during the COVID-19 pandemic across the globe. MHealth is a crucial branch of e-health that provides healthcare services through mobile communication devices and gadgets. MHealth primarily deals with health users' data (e.g., patient, carer, care provider, and laypeople), which is collected through wireless means using smartphones, wearable, and other devices of mHealth. Then, the collected data is stored in the cloud remotely and can be shared and monitored by healthcare professionals for health-related analysis and diagnosis purposes (Eze et al., 2019). Nevertheless, the technological revolution in smartphones has seized and progressed at a slower pace lately across the globe.

The business value for the mHealth market size has reached USD 70.7 billion in 2022 and is expected to grow by nearly 18% to reach USD 370.7 billion by 2030 (Allied Market Research, 2024). Interestingly, the market growth is driven primarily by the burgeoning market penetration rates of intelligent technologies, the cost reduction of mobile technologies, internet speed significance, and accessible mobile data in the healthcare sector across the globe. Additionally, the demand for the mHealth market increased during the pandemic crisis, particularly after the rise in COVID-19 cases worldwide, which placed emergency calls for social interactions and digital health delivery service solutions that must be adopted at speedier rates than before. The expansion of remote patient monitoring and analysis of patient data are some factors that drive the spread of mobile health technologies. Moreover, the rising awareness of mHealth app availability in application stores (Android, Apple, and others) is expected to drive the growth of the mHealth app market. MHealth technologies have been proven to support patients' care, monitor their vital signs, gather clinical health data, and improve healthy behaviours.

In general, there are numerous remarkable mobile apps through Play Stores due to the advancement of mobile technologies and increased usage of handheld devices with improved wi-fi connectivity, accessible at cost worldwide. Among these applications are health and medical apps, considered the most popular categories as they provide many benefits for all stakeholder groups, i.e., patients, doctors, etc. The most commonly used health apps are fitness apps, which have attracted people's attention during the COVID-19 pandemic as they enabled the "anytime and anywhere workout model," (Zhu & Peng, 2021). Another example is medicine delivery and bill reminder apps, which enable patients not to forget to refill their medications, dosage timings, and quantity. Moreover, preventive care and diagnostic test apps would allow people to schedule lab tests at their convenience and create free reports, sample collections, and consultations with physicians. Also, chronic disease monitoring and tracking apps support patients to track their health vitals regularly and share their health information with their physicians.

Generally, the expected total spending in the Middle East and North Africa ICT sector (MENA) will reach USD 178.1 billion in 2023, growing 3.1% from 2022. The MENA region has the highest penetration rates of mobile markets globally. Nearly half of the 25 MENA countries in the area had unique subscriber penetration rates of 70% or more in 2018. Moreover, it was projected to reach around USD 357 million in 2025, up from nearly USD 264 million in 2019. The mHealth market is valued at USD 1.68 billion in 2022 and is expected to reach USD 7.84 billion by 2027 (Saleh, 2024).

The Gulf Cooperation Council (GCC), as a branch of the MENA region – namely the six states, Saudi Arabia, Oman, UAE, Bahrain, Qatar, and Kuwait – proposed that the digital and technological innovation investments, namely, 5G technology networking, AI, internet of things (IoT) and cybersecurity, have risen dramatically. Moreover, the annual investment in healthcare infrastructure is expected to increase by up to 20%. Furthermore, the GCC governments' expenditures on healthcare sectors are expected to reach over 71 billion dollars by 2025. In contrast, Kuwait makes up nearly 11% of the total project monetary values spent within the GCC countries. Digital transformation is considered a defining success factor and the driver behind the fastest adoptions in the technologically driven era, which is critical to GCC's long-term survival and sustainable developments once there is no dependence on oil revenue. For instance, Kuwait's National Development Plan (2035) vision focused on building a diversified and sustainable economy based on digital infrastructure. Its goal is to transform Kuwait into a regional and global hub for finance and trade. The estimated number of cellular mobile connections will rise from 6.8 million in 2023 to 7.5 million internet connections in 2025. Social media users are 3.59 million, representing 3.7% of the total population. The smartphone has helped people and made their lives easier by providing features and functionalities such as text chat, real-time data sharing, video calls, integrated voice chat messages, etc. These functionalities of smartphones can be integrated into delivering healthcare services as promising solutions for mHealth (Aamir et al., 2018; Alhaimer, 2022; Valdmanis et al., 2015; Yousaf et al., 2020; Zhong et al., 2018). Although mHealth is a promising solution, there are considerable challenges to adopting an application.

The Kuwaiti government faces significant challenges within its healthcare system, including rising expenditures, increased medical errors, low productivity and efficiency, and difficulties meeting international standards. A lack of clear direction regarding funding and investment in e-health projects, particularly in the private sector, and inadequate enforcement of data security laws further complicate the situation. Despite the availability of modern technologies, the population tends to prefer a human touch in healthcare, resulting in fragmented systems among hospitals, pharmacies, and other healthcare units, particularly in the public sector. These issues pressure IT professionals to develop effective information technology solutions that improve healthcare services and educate end-users (Banna & Ottesen, 2018). Additionally, Kuwait's underdeveloped healthcare infrastructure complicates the implementation of advanced health technologies and hampers overall efficiency (Al-Hajerri, 2006; Banna & Ottesen, 2018). Challenges such as waiting times, increasing chronic diseases, and communication gaps between patients and providers hinder real-time health monitoring and follow-ups (Alaslawi et al., 2019). In this context, mobile applications offer a promising solution to enhance accessibility, particularly for remote and underserved populations, while improving health awareness and management. This study emphasises the importance of implementing mHealth apps as a transformative solution for the healthcare sector's challenges, highlighting the diverse concerns of various end-user groups to improve healthcare outcomes. The current study recognises the exact nature of the effect of information technologies infrastructure as one of the milestone solutions in the healthcare sector that could be substantial reform and even revolutionary. Additionally, numerous needs may be sprouting around information technologies and mHealth apps. For this reason, it is critical to understand the issue from the breadth and depth of information required by different groups of end-users, which might lead to more effective and efficient healthcare outcomes.

Therefore, this research aims to explore the mHealth issue in Kuwait by drawing on existing and related research and models of mHealth adoption to understand the factors that influence the use of mHealth apps by lay users in Kuwait. This need emerged due to the limited studies that examined the solutions for information technology applications in the Mena region, including the GCC region, particularly Kuwait. Hence, there is an urgent need to carry out an empirical study in the context of Kuwait. Specifically, the aim of this study is twofold:

1. to identify and highlight the impact of factors that contribute to the use of mHealth apps by lay users in Kuwait and
2. to validate a model of mHealth apps used by lay users in Kuwait.

It is worth noting that users of mHealth apps include diverse groups, such as patients, family members, carers, nurses, health professionals, and lay users. However, the study primarily focuses on lay users, who are often vulnerable and frequently overlooked by researchers and health technology providers (Alzougool, 2024). This focus allows a broader understanding of their experiences and perspectives (Sharma et al., 2022). Moreover, "user" aligns with industry terminology, enhancing the study's relevance within the tech and health sectors (Mohr et al., 2017). This choice provides a more nuanced perspective on individuals' interactions with mHealth apps. Recognising lay users' unique challenges is essential, as limited access to healthcare resources and technology can hinder their effective use of mHealth apps (Wang & Qi, 2021). By centring on lay users, the study advocates for increased attention and resources to address their needs within the mHealth landscape (Gonzalez et al., 2020).

Additionally, this study's primary distinction and contribution is its focus on validating a conceptual model for mHealth adoption in Kuwait using empirical quantitative data from lay users, contrasting with previous research that explored various global contexts. For instance, Rajak and Shaw (2021) investigated trust and privacy concerns in India, while Uncovska et al. (2023) analysed factors influencing the acceptance of reimbursed mHealth apps in Germany. In contrast, this study applies these factors to Kuwait's healthcare landscape, providing context-specific insights and highlighting the experiences of lay users, who are often vulnerable and overlooked by researchers and health technology providers. Additionally, this study differs from the work of Banna and Ottesen (2018), who developed a conceptual model based on qualitative data from 30 participants to identify factors affecting mHealth app usage among Kuwaiti consumers. In contrast, this study validates this model with empirical quantitative data collected from a larger sample of lay users in Kuwait. By quantitatively testing the model, this research offers a more robust evaluation of predictive factors that influence the usage of mHealth apps. Furthermore, this study emphasises lay users' experiences, a demographic frequently underrepresented in research and often overlooked by health technology providers.

LITERATURE REVIEW

The Technology Acceptance Model (TAM), developed by Davis (1989), is a fundamental framework that explains individuals' acceptance and use of new technology, particularly relevant for understanding the adoption of health communication interventions, including mHealth apps. Initially, TAM focused on two main factors: PU and PEU. A modified version of TAM introduces additional factors, such as SN, which encompasses the impact of social pressure from friends, coworkers, supervisors, and significant others on the intention to adopt mHealth apps (Lee et al., 2011; Venkatesh et al., 2003). Another vital addition is PBC, derived from the theory of reasoned action (TRA) and the theory of planned behaviour (TPB), which reflects individuals' perceived control over the outcomes associated with using technology. Additionally, PT is crucial for assessing the intention to adopt mHealth apps as it relates to users' concerns about the safety and privacy of their data. The Extended TAM Models, including UTAUT1, further expand on TAM by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Finally, UTAUT2 builds on UTAUT1 by adding new factors such as hedonic motivation, price value, and habit to improve predictions of technology use in consumer environments (Venkatesh et al., 2012). These models comprehensively understand the factors influencing technology adoption (Table 1). Several sectors have significantly utilised these models to solve technology adoption behaviour problems (Spatar et al., 2019).

Table 1. A summary of the critical models related to technology acceptance and adoption

Model	Description	Key factors	References
TAM	A foundational framework explaining individuals' acceptance and use of new technology, particularly relevant for health communication interventions, including mHealth apps.	PU, PEU	Davis (1989), Venkatesh and Davis (2000)
Modified TAM	Introduces additional variables to enhance understanding of technology adoption across contexts.	SN, facilitating conditions.	Lee et al. (2011), Venkatesh et al. (2003)
UTAUT1	Expands on TAM by including factors that further explain technology acceptance and usage.	Performance expectancy, effort expectancy, SN, facilitating conditions	Venkatesh et al. (2003)
UTAUT2	Further extends UTAUT1 by adding new factors for better predictions of technology use in consumer contexts.	Hedonic motivation, price value, habit	Venkatesh et al. (2012)
TRA	TRA posits that an individual's intention to perform a behaviour is influenced by their attitudes toward the behaviour and subjective norms.	Attitude toward the behaviour, SN	Ajzen and Fishbein (1975)
TPB	TPB extends TRA by incorporating perceived behavioural control, acknowledging that individuals may have varying degrees of control over their behaviour.	Attitude toward the behaviour, SN, PBC	Ajzen (1991)

Several researchers have explored the effectiveness of mHealth for the context within several countries across the globe and indicated different adoption rates for each region, as revealed in Table 2. Moreover, mHealth studies have been emphasised significantly in North America, Southwest Asia, Europe, China, Africa, and Turkey. However, it was low in the MENA region, namely Jordan, Egypt, and Yemen. A pilot study conducted by Banna and Ottesen (2018) to evaluate various end-users' viewpoints on mHealth apps utilised TMA and Q methodology via a relatively small sample size of 30 participants. The study found that PU and PEU are the main driving factors behind the escalating adoption of mHealth apps. Therefore, this indicates that the reviews of work for adopting mHealth are still in their infancy stage in GCC, explicitly Kuwait.

Due to limited studies examining the information technologies applications solutions in the Middle East and African region (Mena region), including the GCC region, particularly Kuwait, this paper sought to explore the use of mHealth apps among users. The existing study recognises the exact nature of the effect of information technology infrastructure as one of the milestone solutions in the healthcare sector that could create substantial reform and even revolution. Additionally, numerous needs may be sprouting around information technologies and mHealth apps. For this reason, it is critical to understand the issue from the breadth and depth of information required by different groups of end-users, which might lead to more effective and efficient healthcare outcomes. This study intends to understand the various requirements and provide insights into possible end-users of information technology solutions, i.e., mHealth apps.

Table 2. Available literature on mHealth apps

Author/s	Origin	Model	PU	PEU	PBC	SN	PT
See and Atan (2021)	Malaysia	TAM	X	X			
Al-Azzam et al. (2019)	Jordan	UTAUT2				X	
Krisdina et al. (2022)	Indonesia	TAM & ISSM	X	X			
Yee et al. (2019)	Malaysia	Extended TAM	X	X		X	
Beldad and Hegner (2018)	German	Extended TAM	X	X		X	X
Dou et al. (2017)	China	Extended TAM	X	X		X	X
Salgado et al. (2020)	Portugal	UTAUT2	X	X	X		
Palos-Sanchez et al. (2021)	Spain	Extended TAM	X	X			
Faqih and Jaradat (2015)	Jordan	Extended TAM	X	X		X	X
Alalwan et al. (2018)	Jordan	Extended TAM	X			X	
Alam et al. (2018)	Bangladesh	UTAUT2	X				
Alloghani et al. (2015)	UAE	Modified TAM	X	X			X
Deng et al. (2018)	China	Extended TAM	X	X			X
El-Wajeeh et al. (2014)	Egypt & Yemen	Extended TAM	X	X		X	X
Nusairat et al. (2021)	Jordan	Extended TAM	X	X		X	X
Banna and Ottesen (2018)	Kuwait	TAM	X	X	X	X	X
AlSuwaidi and Moonesar (2021)	UAE	TAM	X	X			
Rajak and Shaw (2021)	India	Extended TAM	X	X	X	X	X
Akdur et al. (2020)	Turkey	Extended TAM	X	X			X
Klaver et al. (2021)	Netherlands	Extended TAM					X
Hoque (2016)	Bangladesh	Extended TAM	X	X	X	X	
Hoque and Sorwar (2017)	Bangladesh	UTAUT				X	
Zayyad and Toycan (2018)	Nigeria	TAM	X				
Balapour et al. (2019)	USA	Modified TAM				X	
Uncovska et al. (2023)	Germany	UTAUT2	X	X	X	X	X

In summary, the adoption factors examined by previous studies are related to four contexts: individual, system, social pressure, and organisational context. This research contributes to the existing bodies of literature in many ways: (i) provides an understating and knowledge of health informatics on mHealth apps usage and how it is associated with technological, social, and functional factors in the context of developing countries; (ii) provides an essential guide to the imminent development of mobile technologies from the views of patients' needs, wants and requirements as the mobile technologies become widely spread across a variety of sectors accompanied by increased demands on digital products and services, (iii) explore an individual adoption should be conducted by considering the examinations of two focal constructs by reflecting on the individual cognitive construct and individual behavioural construct, and (iv) smears TAM method to measure cognitive construct by using PU, PEU, PBC, SN and PR domains. Therefore, the following section aims to explain each factor influencing the adoption of mHealth.

THEORETICAL FRAMEWORK AND HYPOTHESES

This study builds on established mHealth adoption models, notably the research by Banna and Ottesen (2018), who identified five predictive factors affecting mHealth app usage among Kuwaiti consumers through qualitative data from 30 participants: PU, PEU, PBC, PT, and SN. This study validates this model (Figure 1) using quantitative data from a larger sample of lay users in Kuwait, setting this research apart from prior studies that examined various global contexts, such as Rajak and Shaw (2021), who investigated trust and privacy in India, and Uncovska et al. (2023), who looked into reimbursed mHealth apps in Germany. Unlike Banna and Ottesen (2018), this quantitative approach comprehensively evaluates these predictive factors, providing valuable insights into Kuwait's unique healthcare landscape. Furthermore, the study emphasises lay users' experiences, a demographic often underrepresented in research and neglected by health technology providers. The five factors are described below.

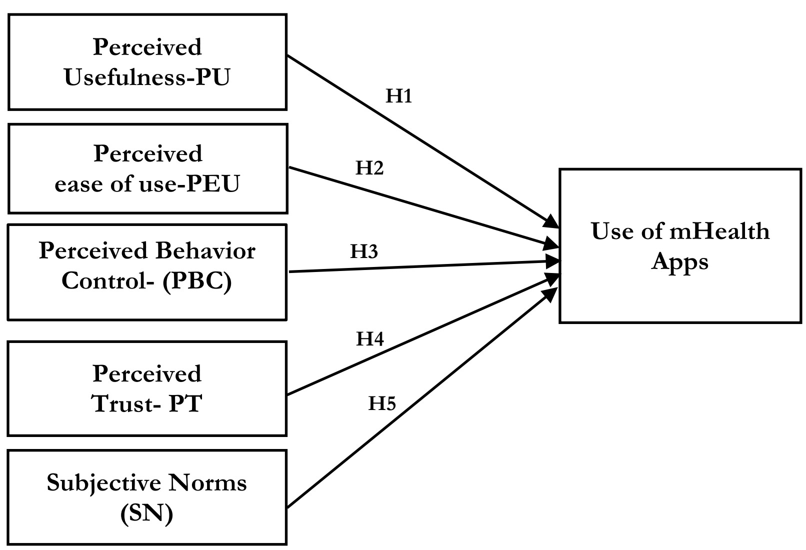

Figure 1. The research model

PERCEIVED USEFULNESS (PU)

PU is defined as the degree to which users believe new mHealth apps are beneficial. Hence, the users think that information system (or mHealth) enhances their job performance and health-related outcomes. Several existing studies have demonstrated a positive correlation between PU and intention to use new technology such as online or e-banking and mobile banking, e-learning, e-ticketing, e-government, and others (Ahmad, 2018; Al-Adwan, 2024; AlHadid et al., 2022; Altamimi et al., 2024;

Banna, 2022; ElKheshin & Saleeb, 2016; Fei et al., 2023; Ly & Ly, 2022; Shankar, 2021; Syarifudin et al., 2018). In the context of mHealth, research also found that PU is an essential determinant for the adoption of mHealth apps since the end users consider its benefits (Akdur et al., 2020; Al-Adwan, 2019; Alloghani et al., 2015; AlSuwaidi & Moonesar, 2021; Beldad & Hegner, 2018; Chau & Hu, 2002; Deng et al., 2018; Dou et al., 2017; El-Wajeeh et al., 2014; Faqih & Jaradat, 2015; Fei et al., 2023; Hoque, 2016; Hoque & Sorwar, 2017; Klaver et al., 2021; Krisdina et al., 2022; Nusairat et al., 2021; Palos-Sanchez et al., 2021; Rajak & Shaw, 2021; Salgado et al., 2020; Yee et al., 2019; Zayyad & Toycan, 2018). Therefore, we proposed the following hypotheses about PU:

H1: PU positively influences the use of mHealth apps.

Perceived Ease of Use (PEU)

Current research defines PEU as the extent to which a user (patient, doctor, nurse, carer...etc.) believes mHealth service requires little effort. It was found that PEU positively affects the use of technology. In a nutshell, various reviews of work have shown that "PU" played a crucial role in understating the market predictions on the attitude and behaviour of typical users of digital resources, i.e., mHealth service (Akdur et al., 2020; Al-Adwan, 2019, 2024; Alloghani et al., 2015; AlSuwaidi & Moonesar, 2021; Beldad & Hegner, 2018; Chau & Hu, 2002; Deng et al., 2018; Dou et al., 2017; El-Wajeeh et al., 2014; Faqih & Jaradat, 2015; Fei et al., 2023; Hoque, 2016; Hoque & Sorwar, 2017; Klaver et al., 2021; Krisdina et al., 2022; Nusairat et al., 2021; Palos-Sanchez et al., 2021; Rajak & Shaw, 2021; Salgado et al., 2020; Yee et al., 2019; Zayyad & Toycan, 2018). Therefore, we proposed the following hypotheses about PEU:

H2: PEU positively influences the use of mHealth apps.

Perceived Behaviour Control (PBC)

PBC refers to the degree to which a person feels how much control and confidence a person has about being able to perform or engage in a behaviour (Ajzen, 1991). This construct was derived from the TRA and TPB, which link behaviour, beliefs, and attitudes (Ajzen, 1991; Armitage & Conner, 2001). In the TPB, Ajzen (1991) suggested that PBC belief stems from two sources, namely, an individual inner force, i.e., self-sufficiency, prior expertise, and skills, and prior knowledgeability, and the second source is the outer force that controls external conditions, namely information system accessibility and availability and technical assistance availability. For instance, a person needs to evaluate higher relative advantage and higher PBC after a specific attitude is formed. Therefore, this factor shapes a person's behavioural intention to use a technology when a habit is developed (Al-Adwan et al., 2024; Kiriakidis, 2015; Limayem et al., 2007; Venkatesh et al., 2012; Wu et al., 2022). Furthermore, a habit means the extent to which an activity repeatedly becomes, automatically and spontaneously, after a period of experience and usage. However, it is noted that few researchers investigated this construct from mHealth apps. Salgado et al. (2020), Balapour et al. (2019), Uncovska et al. (2023), and Hoque (2016) found that PBC plays an influential role in the intention to adopt mHealth apps. Therefore, we proposed the following hypotheses about PBC:

H3: PBC positively influences the use of mHealth apps.

Perceived Trust (PT)

The concept of PT was conceptualised from the uncertainty related to end-user action toward purchasing new brands or products (Cunningham, 1967). Since the construct was utilised in the adoption prediction framework of any new element, including e-service, it helps adopt mHealth apps (Dwivedi et al., 2016; Miller & Griffy-Brown, 2018). Moreover, various researchers reported different types of risk associated with online services, and consumers were worried about the security issues related to technologies (Ba & Pavlou, 2002; Kala et al., 2024; Miller & Griffy-Brown, 2018). Earlier reviews of work have defined perceived security risk from fraud related to product quality (Altamimi et al., 2024; Hirunyawipada & Paswan, 2006; Im et al., 2008; Martins et al., 2014). The perceived security risk is measured in multiple dimensions- security, performance, psychological, trust, and so forth (Miller & Griffy-Brown, 2018). In the literature, the majority of researchers indicated the significant, influential role of perceived trust on the adoption intentions for mHealth apps (Akdur et al., 2020; Alloghani et al., 2015; Deng et al., 2018; Dou et al., 2017; El-Wajeeh et al., 2014; Faqih & Jaradat, 2015; Klaver et al., 2021; Nusairat et al., 2021; Rajak & Shaw, 2021). Therefore, we propose the following hypotheses about PT:

H4: PT positively influences the use of mHealth apps.

Subjective Norm (SN)

Researchers use SN to refer to social influence interchangeably. SN is nothing but how a user's perception is influenced by their surroundings of people. Social surrounding factors are crucial for understanding the utilisation of technologies in our daily lives. The SN factor can be conceptualised as the level of users' understanding of the importance of mHealth apps. Moreover, this societal construct explains the importance of society as a driver behind the adoption of mHealth apps among people as it elevates the level of confidence and shapes the perceptions towards the adoption of any technology. This factor implies that the impact of their social circles influences future users' adoptions and intentions. Venkatesh and Davis (2000) confirmed the crucial role of SN on behavioural intention and attitudes. Likewise, various researchers have confirmed a positive relationship between SN and the use of mHealth apps (Alalwan et al., 2018; Al-Azzam et al., 2019; Beldad & Hegner, 2018; Dou et al., 2017; El-Wajeeh et al., 2014; Faqih & Jaradat, 2015; Hoque, 2016; Maliwichi & Chigona, 2022; Nusairat et al., 2021; Rajak & Shaw, 2021; Yee et al., 2019). Therefore, we propose the following hypothesis:

H5: SN positively influences the use of mHealth apps.

Method

Research Instrument

A cross-sectional study was carried out among people in Kuwait to achieve the study objectives. The questionnaire was used to obtain data from users in Kuwait regarding factors that impact their use of mHealth apps. The online self-administered, voluntary, and anonymous questionnaire consisted of two parts, including:

- demographic information such as sex, age, job role, education, ethnicity, sector employment, hourly spent using the internet, health status, devices used, online searching, frequency of searching health information, consulting primary health providers); and
- a five-point Likert scale self-administered items to measure the five independent factors (i.e., PU, PEU, PBC, PT, and SN) and one dependent variable (i.e., use of mHealth apps) where each question was anchored where five indicates a "strongly agree" and -5 indicates "strongly disagree" for a total of 34 statements which all were adopted from previously validated studies (Chaudhuri & Holbrook, 2001; Davis, 1989; Johnston & Warkentin, 2010; Sun et al., 2013).

Before public distribution, a pilot test was conducted with academics to gather feedback on the draft questionnaire for improvement. The feedback was generally positive, with participants finding the content straightforward and valuable, the objectives well-defined, the content sufficient and accurate, and the structure easy to follow.

Sampling Procedures and Size

Because this study aimed to collect data from lay users who use mHealth apps, a screening question was included to identify if participants have used any mHealth apps in the past. Therefore, a purposive sampling method utilising convenience and snowballing sampling techniques was used in which all the respondents were lay users. A minimum sample size of 219 responses was needed for proper analysis, as suggested by Cohen (2013). This was calculated using the G*power 3 program considering an intermediate effect size of 0.06, significance level of 0.05, power of 0.95, and number of independent variables of 4. Two hundred and twenty-five users participated in this study and were used in the analysis.

Data Collection and Procedure

A questionnaire link was created using Google Forms and remained open for about two months. The data collection took place from May to July 2023. Participants were recruited through an email announcement with a link to the online questionnaire. Initially, we asked students, instructors, and staff at the Arab Open University (AOU) at the Kuwait branch. Then, after they answered the questionnaire, we asked them to distribute the link to the online survey among their friends, family members, and relatives. The questionnaire link was also distributed on social media platforms like Instagram, LinkedIn, and Facebook. The questionnaire respondents must be at least 25 to participate in this study. The nature and purpose of the study were explained to them, and it was emphasised that they chose the answer they felt was right. The instructions for completing the questionnaire were given on a cover page to avoid misunderstanding the issue. Participants were assured anonymity and confidentiality, and participation was voluntary. The questionnaire completion took approximately less than 15 minutes.

Data Analysis

Data were analysed using the statistical package for social science (SPSS) software (version 19.0). Descriptive statistics were computed to summarise the data, with means, standard deviations, frequencies, and percentages calculated where applicable. The scales were evaluated by factor analysis and Cronbach's alpha. Pearson correlation test was used to explain the relationship between the four identified factors and the use of mHealth apps. A multi-regression analysis explored the factors affecting the use of mHealth apps. Statistical significance was established at $p < 0.05$ for all tests. In addition, Harman's factor method for measuring common method bias was used to check whether variance in the data can be primarily attributed to a single factor (Podsakoff et al., 2003). The single factor accounted for 29.9% of the variance found in the data. This is below the cut-off of 50%, suggesting no systematic standard method bias in the study (Harman, 1976).

Findings

Demographic Data

There is no gap between female and male respondents (50.7% and 49.3%). The majority of the sample was 79%, aged between 25-34; nearly 18% were aged between 34 and 44, and less than 2% were aged between 45 and 66. Most respondents had bachelor's degrees, half had high school and college diplomas, while less than 3% had graduate degrees. Half of the respondents were Kuwaitis, and the other half were non-Kuwaitis from various origins, such as other Arabs, Asians, Europeans, Australians, and Americans. Most respondents were students, 24% were health professionals, and less than 20% were patients with their relative carers. Nearly 40% were employed in the private sector versus only 22% in the public/government sector, whereas 18% were unemployed, 9% owned family businesses, and 11% were self-employed. Almost 70% spent 1-6 hours online daily, whereas 25% spent more than 6 hours. Over 92% rated their health as excellent, very good, and sound. More than 90% were using smartphones to search for health information, while the rest of the respondents were using various devices such as laptops, tablets, and desktops. More than 57% of respondents have themselves, family members or relative chronic illnesses. Almost half were light seekers, and only 36% were heavy health information seekers.

MHealth Applications Used by Lay Users in Kuwait

Table 3 shows the most used mobile health apps among the respondents in Kuwait. The table indicates that Apple Health is the most frequently used app, which 29.2% of participants utilised. This shows its strong market presence and appeal due to its integration with other Apple products and comprehensive health monitoring features. Following this, Q8seha, a local health app developed by Kuwait's Ministry of Health (MOH) in 2020, was used by 20.5% of participants, reflecting the public's engagement with government-provided digital health services. It is primarily developed to provide eHealth services for all citizens and residents using a one-stop portal. Apple Fitness ranked third at 9.9%, likely driven by users' interest in fitness-focused applications. Immune-MOI, developed by the Ministry of Interior (MOI) for COVID-19 vaccination registration and tracking, was used by 8.8% of participants, underscoring the significance of health and immunisation tracking post-pandemic. This app was used to register for the coronavirus vaccines and check the doses during the COVID-19 era. Both Huawei Health and Samsung Health had a similar adoption rate of 6.4%, indicating a preference for Android-based health apps among a smaller segment of users. This distribution suggests that while global tech giants like Apple dominate the mHealth space, local government apps and Android-based solutions maintain a notable user base, creating a balanced health app ecosystem that caters to diverse needs.

Table 3. Common mHealth apps used in Kuwait (n=171)

MHealth apps	Freq. (%)	Comments
Apple Health	50 (29.2%)	It helps measure the duration of movement in daily activities and determine whether the body is active or inactive.
Q8seha-MOH	35 (20.5%)	It helps in emergencies, view the status of the medical report, pay the fees, view the report, schedule clinical appointments, search for clinics and hospitals, and sick leave (recently activated here)
Apple Fitness	17 (9.9%)	It offers personalised workouts, real-time fitness tracking, and seamless integration with Apple devices. It includes progress rings, group workouts, and comprehensive fitness and stress management mindfulness sessions.
Immune-MOI	15 (8.8%)	People used it during the pandemic to check and register for new doses to protect us from it.
Huawei Health	11 (6.4%)	It calculates time and calories burned while walking outside and helps monitor heart rate. It also provides reminders to move after long periods of inactivity.
Samsung Health	11 (6.4%)	It tracks daily activity, exercise, sleep, and nutrition, offering personalised workout plans and heart rate monitoring. It is integrated with Samsung Galaxy Watches and provides accurate health metrics, guided meditation, stress tracking, and social features for friendly challenges.

Factors Affecting the Use of MHealth Applications

Factor analysis on the multi-item measures was conducted to identify the underlying factors of these items. Factor analysis was used to examine whether or not the items load on the specified factors as predicted. Several different representations were explored before deciding on the solutions. The overall and individual item measures of sampling adequacy were high, indicating the appropriateness of the data for factor analysis. Both the scree plot and parallel analysis test suggested a four-factor solution (Table 4). The first factor has eleven items and had loadings of 0.502 or more significant on this factor. It accounts for 27.7% of the variance. Cronbach alphas a were checked for the reliability of each factor and rendered a result of 0.962 for Factor 1. The items of this factor imply that participants use mHealth apps because they are confident and perceive these applications as easy to use. Therefore, this factor is labelled as perceived ease of use and behaviour control (PEUBC). The second factor has six items and had loadings of 0.644 or more significant on this factor. It accounts for 19.2% of the variance. Cronbach was 0.925 for this factor. The items of this factor imply that participants use mHealth apps because they trust these applications and consider them less risky. Therefore, this factor is labelled as PT following previous literature. The third factor has seven items and had loadings of 0.521 or more significant on this factor. It accounts for 18.9% of the variance. Cronbach was 0.932 for this factor. The items of this factor imply that participants use mHealth apps because of their usefulness. Therefore, this factor is labelled as PU following previous literature. The last factor has two items and had loadings of 0.611 or more significant on this factor. It accounts for 9.4% of the variance. Cronbach was 0.764 for this factor. The items of this factor imply that participants use mHealth apps because their social circles influence them to use these applications. Therefore, this factor is labelled as SN following previous literature.

Table 4. Factor loadings for the final four-factor solution

Factors	1	2	3	4
Factor 1: PEUBC				
Item12 – MHealth is clear and understandable	.792			
Item13 – MHealth apps are easy to use	.778			
Item9 – MHealth is flexible to use/interact with	.748			
Item19 – I have the knowledge to use the mHealth system	.716			
Item14 – Easy to do tasks with mHealth apps	.716			
Item11 – MHealth requires low mental effort	.660			
Item15 – The m – mHealth system is convenient for me	.657			
Item10 – MHealth increases the quality of care	.656			
Item18 – There is an availability of technical assistance	.576			
Item17 – The mHealth system is compatible with other systems	.574			
Item16 – I'm able to use the mHealth system for patient care and management	.502			
Factor 2: PT				
Item26 – I trust health information remains confidential with mHealth apps		.745		
Item25 – I believe that mHealth apps are more secure		.738		
Item27 – I trust the mHealth technology to be free of risk		.730		
Item28 – I have no privacy concerns using mHealth apps		.697		
Item22 – Subordinates at work think I should use the mHealth system		.657		
Item24 – I trust mHealth apps		.644		
Factor 3: PU				
Item1 – MHealth apps support critical aspects of my healthcare			.756	
Item 2 – MHealth enables better decisions based on a better evidence-based environment.			.733	
Item6 – MHealth is helpful for the job (or task)			.674	
Item5 – MHealth enhances the effectiveness of job (or work)			.661	
Item3 – MHealth improves patient care and management			.639	
Item 7 – MHealth increases my productivity.			.574	
Item4 – It is easy to become skilful with the mHealth system			.521	
Factor 4: SN				
Item20 – Senior management of the hospital has been helpful with mHealth apps				.706
Item21 – My family doctor, who influences my behaviour, thinks I should use mHealth apps				.611
Variance explained (%)	**27.7**	**19.2**	**18.9**	**9.4**

Therefore, four factors that could affect the use of mHealth apps were identified: PT, PEUBC, PU, and SN. Key features of these factors are provided in Table 5, which shows the number of items, mean, standard deviation, and Cronbach's alpha of each factor. As shown in Table 5, participants nearly equally identified the four factors. Participants used mHealth apps. They trusted these applications because they were confident and perceived them as easy to use, because of their usefulness, and because their social circles influenced them to use them.

Table 5. Number of items, mean, standard deviation, and Cronbach's alpha of each factor

Identified factors	No. of items	Mean	SD	Cronbach's alpha
Perceived ease of use behaviour control	11	3.48	.863	.962
Perceived trust	6	3.33	.874	.925
Perceived usefulness	7	3.47	.830	.932
Subjective norms	2	3.27	.909	.764
Use of mHealth apps	6	3.41	.922	.955

The Relationship Between the Identified Factors and the Use of mHealth Applications

The Pearson Correlation Test in Figure 2 explained the relationship between the four identified factors and the use of mHealth apps. The findings show a significant relationship between all four identified factors and the use of mHealth apps. Therefore, these four factors do influence the use of mHealth apps.

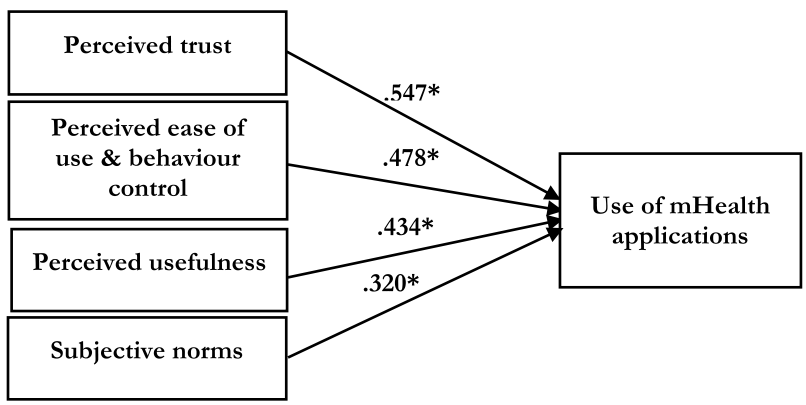

Figure 2. The relationship between the identified factors and the use of mHealth apps (after doing factor analysis) (n = 225)

ANOVA test for regression analysis shows a significant relationship between the independent variable (four identified factors) and the dependent variable (use of mHealth apps) at the 0.001 significant levels. The analysis in Table 6 shows that PT (Model 1) gives a significant result with $F = 95.153$, $p < 0.001$. The combination of PT and PEUBC (Model 2) also provides a significant result ($F = 124.074$, $p < 0.001$). Moreover, the combination of PT, PEUBC, and PU (Model 3) gives a significant result ($F = 185.859$, $p < 0.001$). Furthermore, PT, PEUBC, PU, and SN contribute more to using mHealth apps. Model 4 gives a significant result ($F = 247.655$, $p < 0.001$).

In addition, the multiple regression test shows that (Table 7) perceived trust significantly contributes to 29.9% of the variance ($R2 = 0.299$) towards using mHealth apps by participants. This means that PT ($B = 0.547$, $p < 0.001$) is the main contributor that caused participants to use mHealth apps. The combination of both PT ($B = 0.547$, $p < 0.001$) and PEUBC ($B = 0.478$, $p < 0.001$) increases the significant contribution to 52.8% ($R2 = 0.528$). However, with the combination of predictors between PT ($B = 0.547$, $p < 0.001$), PEUBC ($B = 0.478$, $p < 0.001$), PU ($B = 0.434$, $p < 0.001$), and SN (B =

0.320, $p < 0.001$), the significant contribution value of variance towards using mHealth apps by participants increases to 81.8%. Therefore, it can be concluded that the four identified factors (i.e., PT, PEUBC, PU, and SN) were the main contributors that caused participants to use mHealth apps.

Table 6. Analysis of variance of factors affecting the use of mHealth apps (n = 225)

Model	Sum of squares	DF	Mean square	F	Sig.
1					
Regression	66.994	1	66.994	95.153	.000*
Residual	157.006	223	.704		
Total	224.000	224			
2					
Regression	118.229	2	59.114	124.074	.000*
Residual	105.771	222	.476		
Total	224.000	224			
3					
Regression	160.417	3	53.472	185.859	.000*
Residual	63.583	221	.288		
Total	224.000	224			
4					
Regression	183.294	4	45.823	247.655	.000*
Residual	40.706	220	.185		
Total	224.000	224			

Note: *$p < 0.001$

Table 7. Coefficient regression of factors affecting the use of mHealth apps: multi-regression analysis, stepwise method (n = 225)

Model	B	Beta	T	Sig.
1				
Perceived trust (low risk)	.547	.547	9.755	.000*
2				
Perceived trust (low risk)	.547	.547	11.858	.000*
Perceived ease of use & behaviour control	.478	.478	10.370	.000*
3				
Perceived trust (low risk)	.547	.547	15.260	.000*
Perceived ease of use & behaviour control	.478	.478	13.345	.000*
Perceived usefulness	.434	.434	12.109	.000*
4				
Perceived trust (low risk)	.547	.547	19.028	.000*
Perceived ease of use & behaviour control	.478	.478	16.640	.000*
Perceived usefulness	.434	.434	15.100	.000*
Subjective norms	.320	.320	11.119	.000*
	R	**R^2**	**Adjusted R^2**	
1	.547	.299	.296	
2	.727	.528	.524	
3	.846	.716	.712	
4	.905	.818	.815	

Note: *$p<0.001$

Summary of hypotheses testing:

H1: PU positively influences the use of mHealth apps – supported.
H2 & H3: PEU and PBC jointly positively influence the use of mHealth apps – supported
H4: PT positively influences the use of mHealth apps – supported.
H5: SN positively influences the use of mHealth apps – supported.

DISCUSSION

According to the findings of this study, the most used mHealth apps in Kuwait were Apple Health, followed by Q8seha, with Apple Fitness and Immune-MOI ranking third and fourth, respectively. The preference for Apple Health is due to its features and integration with Apple devices, while Q8seha's second place reflects public engagement and the Ministry of Health's promotion. This influence is also evident in Immune-MOI, which focused on vaccination tracking during the pandemic. These results show a diverse health app landscape where global leaders like Apple coexist with local solutions, highlighting the importance of functionality, user experience, and integration in driving app popularity. Interestingly, more than three-quarters of consumers were satisfied with these applications.

The results identified four key factors influencing mHealth app usage: PT, PEUBC, PU, and SN, consistent with previous studies (e.g., Dou et al., 2017; Hoque, 2016; Nusairat et al., 2021; Rajak & Shaw, 2021; Uncovska et al., 2023). These factors suggest that users are more likely to use mHealth apps if they trust them, find them easy to use, value them for their health needs, and are recommended by others. This result underscores the complexity of user engagement with mHealth apps, indicating that multiple interrelated factors drive usage. Understanding these influences can help developers and policymakers design and promote mHealth solutions that cater to user expectations, enhancing adoption and engagement. Significant relationships were found between all four factors and mHealth app usage. This suggests that users consider these aspects when deciding whether to adopt and engage with health apps, making them essential for successful app design and promotion. PT emerged as the most influential factor, highlighting the need for developers to prioritise privacy, confidentiality, and security to build user confidence. This suggests that trust-building measures are crucial in promoting the widespread use of mHealth apps.

Specifically, hypothesis H1 examined the positive influence of PU on mHealth app usage, and the results confirm it as a significant predictor. This finding aligns with previous studies (e.g., Krisdina et al., 2022; Rajak & Shaw, 2021; Yee et al., 2019; Zayyad & Toycan, 2018) and reinforces the TAM's relevance. One explanation for this is that respondents view mHealth apps as valuable tools that offer various benefits, such as improved self-care management, better health decisions, enhanced communication with professionals, and more effective service delivery. In other words, when users perceive mHealth apps as beneficial, they are more likely to use them. Consequently, developers and marketers should highlight these benefits to increase user adoption and engagement while considering demographic and experiential factors that may influence perceived usefulness in future research.

The results for hypotheses H2 and H3 also revealed a significant joint positive influence of PEUBC on the usage of mHealth apps, indicating that these factors together serve as positive predictors of lay users' engagement. This finding aligns with prior research (e.g., Akdur et al., 2020; Balapour et al., 2019; Hoque, 2016; Klaver et al., 2021; Rajak & Shaw, 2021; Salgado et al., 2020; Uncovska et al., 2023). However, it is surprising that these theoretically distinct factors appear to act as a combined predictor in this context. One possible explanation for this unexpected result could be that in practical settings, PEUBC may overlap in their effects. For instance, when users perceive an app as easy to use, they might feel more confident navigating its features, enhancing their sense of control. This interaction suggests that improvements in one area could positively impact the other, ultimately leading to a more favourable user experience. Therefore, mHealth app designers should focus on creating intuitive, user-friendly interfaces that facilitate ease of use and empower users, ensuring that they have the skills and confidence to engage with the technology effectively. Additionally, addressing potential barriers, such as the need for extensive training and technical support, could further enhance user engagement and satisfaction. This finding highlights the need for a holistic approach to mHealth app development that prioritises user experience, reduces barriers, and fosters user confidence, ultimately leading to increased engagement and effectiveness in health management. Furthermore, this unexpected interaction warrants further research to explore the underlying mechanisms of how these factors influence user behaviour in the mHealth context.

Moreover, hypothesis H4 examined the positive influence of PT on the usage of mHealth apps, and the results indicate that PT is a significant positive predictor of lay users' engagement with these applications. This finding aligns with previous research (e.g., Akdur et al., 2020; Alloghani et al., 2015; Deng et al., 2018; Dou et al., 2017; El-Wajeeh et al., 2014; Faqih & Jaradat, 2015; Klaver et al., 2021; Nusairat et al., 2021; Rajak & Shaw, 2021). A possible explanation for this outcome is that when patients and lay users perceive their data as confidential, protected, and secure from risks, they are more likely to utilise these apps. This underscores the critical role of trust in fostering user engagement with mHealth technologies. When users feel assured that their sensitive information is handled responsibly, they are more inclined to adopt and actively use these applications, highlighting the importance of implementing robust security measures and transparent data practices to build trust and encourage more significant usage of mHealth apps. This implies that creating and maintaining user trust is essential for adopting and engaging these technologies. Developers and health organisations must prioritise robust security measures and transparent data handling practices to ensure users feel confident that their personal information is confidential, protected, and free from risks. The non-surprising nature of this result underscores the fundamental role of trust in the acceptance of mHealth technologies, reflecting broader trends in consumer behaviour regarding digital privacy and data security.

Furthermore, hypothesis H5 examined SN's positive influence on mHealth apps' use, and the results indicate that SN is a significant positive predictor of lay users' engagement with these applications. This finding supports the hypothesis and is consistent with previous research (e.g., Alalwan et al., 2018; Al-Azzam et al., 2019; Beldad & Hegner, 2018; Dou et al., 2017; El-Wajeeh et al., 2014; Faqih & Jaradat, 2015; Hoque, 2016; Nusairat et al., 2021; Rajak & Shaw, 2021; Yee et al., 2019). The results suggest that social influences from significant others – such as family, friends, and colleagues – play a crucial role in adopting mHealth apps, as users are likely to follow suit when these individuals endorse or use them. This underscores the need to leverage social networks to promote mHealth apps, indicating that positive recommendations from trusted sources can enhance user engagement. Marketing strategies should, therefore, focus on cultivating a supportive social environment that encourages mHealth app usage. While the influence of SN in technology adoption is acknowledged, the extent of its impact on mHealth app usage, particularly in an era of individual choice and privacy concerns, may not align with prior expectations, making this result somewhat surprising.

LIMITATIONS AND FUTURE RESEARCH

It is worth noting that this study has several limitations.

(1) Sample size and procedure, which eliminated its generality. The sample may not reflect the national trends because only 225 surveys were completely filled up using non-probability sampling. Therefore, because of the small sample size of this study, it cannot be claimed that the findings are generalisable to all people in Kuwait. It would be advantageous to conduct a more extensive scale survey over a more comprehensive geographical range.

(2) The sample did not investigate the perception of those younger than 25 years old as part of Generation Z, which is considered to be the "digital native" young segment of the population that grew up with social media and mobile applications.

(3) However, this study applied the TAM model. Hence, other factors were not included, such as cost concerns or price value of the mHealth app, life quality improvement, job relevance, and continuous usage behaviour.
(4) Finally, this study has not investigated the low adoption and diffusion rates of mHealth apps among people in Kuwait despite high rates of usage of mobile applications in various regulated sectors such as banking and food, which is worth future explorations.

Future studies must apply probability sampling techniques and increase the sample size to generate more reliable and generalisable findings. Additionally, the young age segment must be considered here, and research must be extended to consider the moderating role of demographic factors like age, gender, and educational levels to better understand the adoption of mHealth apps. The model was tested based on a limited number of professionals. Therefore, future research could investigate these adoption factors from medical professionals' perspectives and compare the results. One notable limitation of this study is that lay users reported utilising both built-in mHealth apps from major platforms and government-provided apps. This dual usage may affect the overall results, as the inherent differences between these two categories make them somewhat incomparable. Built-in applications often leverage advanced technology and user data to offer personalised experiences, while government apps are typically designed to focus on public health initiatives and accessibility. Consequently, users' experiences and perceptions may vary significantly based on each application type's distinct features and functionalities. Moreover, the differing economic models—where government apps are usually free and privately developed apps may require payment—add another layer of complexity that could influence user trust, value perception, and ease of use. Therefore, the findings may not fully capture the nuanced dynamics of user usage of both application types, highlighting the need for future research to comprehensively explore this distinction in greater depth to understand user behaviour and adoption patterns.

CONCLUSION, IMPLICATIONS, AND RECOMMENDATIONS

The study aimed to identify and examine the factors influencing lay users' usage of mHealth apps in Kuwait and to validate a model of mHealth app usage among these consumers. A quantitative study was conducted to achieve the study objectives. The study showed that lay users mostly used Apple Health and Q8Seha applications in Kuwait. Moreover, four identified factors (i.e., PT, PEUBC, PU, and SN) were the main contributors that caused lay users to use these mHealth apps. PT was the main contributor that caused consumers to use these mHealth apps.

Considering the above results, this study has theoretical and practical implications. For theory, this study employed a quantitative approach to examine the usage of mHealth apps by lay users in Kuwait, thereby contributing to the limited literature on this topic in the Arab Gulf countries, particularly Kuwait. It enriches existing research on mHealth technologies by identifying the social, functional, and technological factors that influence the adoption and success of these health technologies. Furthermore, the findings support the extension of the TAM to include additional factors pertinent to mHealth apps and health contexts. This research also provides a framework for comparing mHealth app usage among lay users in developing and developed countries. Additionally, it responds to calls from scholars (e.g., Jones & Smith, 2020; Khatun et al., 2018) for a deeper understanding of mHealth app usage in developing nations. By investigating these emerging technologies, this study contributes to the growing body of academic literature on mHealth apps utilised by lay users. While previous research, including studies by Rajak and Shaw (2021) and Uncovska et al. (2023), examined various influencing factors, our study validates a model of mHealth app usage that includes variables not extensively explored in existing literature, providing a more nuanced perspective on these factors' interactions. Consequently, this contribution enhances the theoretical framework surrounding mHealth apps and underscores the importance of considering local contexts in examining user behaviour in health technology adoption.

For practice, the results identified four key factors influencing mHealth app usage: PT, PEUBC, PU, and SN. This shows that user engagement is driven by multiple interrelated factors, requiring developers and marketers to prioritise these aspects in their designs and promotions. To increase app usage, developers should focus on user-friendly interfaces, incorporate trust-building features like transparent privacy settings, and highlight the app's benefits through real-world applications and testimonials. To support user confidence, marketing strategies should leverage social norms to enhance credibility and provide educational resources, such as tutorials and FAQs. Implementing feedback mechanisms, tailoring marketing to specific demographics, and integrating apps into healthcare systems will further boost perceived usefulness and adoption. Our research offers guidance for developing patient-centric mHealth apps in developing countries by addressing design and functionality expectations. Developers must prioritise data security and compliance with international regulations, as handling sensitive personal data significantly impacts user perception and continued use. Therefore, maintaining data confidentiality and privacy is essential for driving adoption and trust in mHealth technology.

Since PT is the primary factor driving consumers to use mHealth apps, developers must prioritise data security and privacy. Transparent data management and robust user protection practices are essential for boosting adoption. To build trust, developers should implement strong security measures and communicate these clearly to users, providing detailed information on data handling, privacy policies, and user rights. Ensuring that sensitive personal data is stored and processed securely while adhering to international regulations is crucial for maintaining trustworthiness and encouraging continued app usage. Government support through policies, funding, regulatory oversight, and public awareness initiatives can further enhance trust. Healthcare providers should also integrate mHealth apps into their services, train staff, collect patient feedback, and collaborate with developers to create customised healthcare solutions that address patient needs.

PEUBC highlights the need for user-friendly app design. Developers should focus on intuitive interfaces that reduce navigation effort to enhance engagement and satisfaction. A user-centric approach through usability testing can identify pain points and optimise the experience. Providing educational resources, tutorials, and onboarding sessions can help users navigate the app confidently, especially those less comfortable with technology. Developers should also regularly update the app's functionality to keep it relevant and adapt features to meet the diverse needs of lay users.

PU significantly impacts lay users' willingness to engage with mHealth apps. Developers should highlight the practical benefits of their apps in marketing strategies, using real-life success stories, testimonials, and evidence-based results to demonstrate value and encourage adoption. These findings can also inform the development of new mHealth apps by prioritising patient-centric needs, especially in developing countries, ensuring that design and functionality meet user expectations to enhance PU.

SN is crucial in technology adoption, as social dynamics significantly influence user behaviour. Positive recommendations from peers, family, and healthcare professionals can boost mHealth app uptake. Adding features for users to share experiences or achievements within their social networks can further drive engagement. Developers should collaborate with influencers or healthcare professionals to increase visibility and position the app effectively within social contexts to foster broader acceptance and usage.

In summary, a comprehensive approach that addresses trust, perceived ease of use and behavioural control, perceived benefits, and social influences is essential for promoting the adoption and effective use of mHealth apps among lay users.

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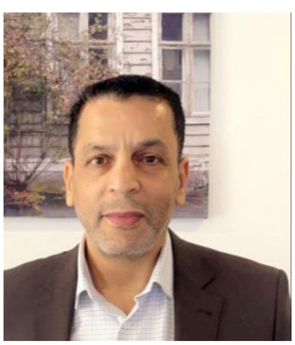

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