Investigating Mobile Health (mHealth) Factors That Influence Technology Acceptance Among Egyptian Patients

التحقيق في عوامل الصحة المحمولة التي تؤثر على قبول التكنولوجيا بين المرضى المصريين

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Abstract:

Purpose – This study explores the mobile health (mHealth) application adoption among Egyptian healthcare consumers, examining the applicability of the unified theory of acceptance and use of technology. The research identifies key predictors of behavioral intentions to mHealth apps and explore how demographic factors moderate the relations.

Design/methodology/approach – Quantitative questionnaires were distributed during January 2024 till June 2025 (using a cross sectional timeframe) digitally, using Google Form, to patients that tired mHealth. 405 respondents were analyzed. The analyses were conducted using structural equation modeling (SEM) Smart PLS.

Findings – This study found that performance expectancy emerged as the strongest predictor of behavioral intention to use mHealth apps ($\beta = 0.497$, $p = 0.000$), followed by Effort Expectancy ($\beta = 0.151$, $p < 0.05$) and Social Influence ($\beta = 0.096$, $p < 0.05$). The model explained 48.2% of variance in behavioral intention. Gender significantly moderated relations of Performance Expectancy and behavioral intention ($\beta = -0.093$, $p = 0.046$) and between Effort Expectancy and behavioral intention ($\beta = 0.131$, $p = 0.002$). Experience moderated the Effort Expectancy-behavioral intention ($\beta = -0.083$, $p = 0.019$).

Practical implications – This study informs the development and implementation of effective mHealth interventions in Egypt. This study identifies the factors that influence mHealth use among Egyptian healthcare consumers to provide practitioners with insights on how to improve healthcare access and outcomes, tailoring mHealth solutions to better meet the needs and preferences of patients, leading to increased adoption and utilization.

Originality/value –The study provides the first comprehensive UTAUT-based analysis of mHealth adoption in Egypt's rapidly evolving digital health landscape, offering evidence-based recommendations for healthcare technology implementation in similar emerging markets with young, digitally engaged populations.

Key Word: Behavior Intentions, Healthcare Consumers, Healthcare Technology, Mobile Applications, UTAUT

الملخص:

الغرض: تستكشف هذه الدراسة تبني تطبيقات الصحة المحمولة بين المستهلكين المصريين في قطاع الرعاية الصحية، من خلال دراسة مدى قابلية تطبيق النظرية الموحدة لقبول واستخدام التكنولوجيا. وتحدد الدراسة العوامل الرئيسية التي تتنبأ بالنوايا السلوكية لاستخدام تطبيقات الصحة المحمولة، كما تستكشف كيف تؤثر العوامل الديموغرافية في تعديل هذه العلاقات.

المنهجية/أسلوب البحث: تم توزيع استبيانات كمية خلال الفترة من يناير ٢٠٢٤ حتى يونيو ٢٠٢٥ (ضمن إطار زمني عرضي) بشكل رقمي عبر نماذج إلكترونية، على المرضى الذين جربوا تطبيقات الصحة المحمولة. تم تحليل إجابات ٤٠٥ مشاركين. أُجريت التحليلات باستخدام نمذجة المعادلات الهيكلية عبر برنامج متخصص.

النتائج: أظهرت الدراسة أن توقعات الأداء كانت أقوى عامل تنبؤي بالنية السلوكية لاستخدام تطبيقات الصحة المحمولة، تليها توقعات الجهد ثم التأثير الاجتماعي. وفسر النموذج ٤٨.٢٪ من التباين في النية السلوكية. كما أن النوع الاجتماعي عَدّل بشكل ملحوظ العلاقة بين توقعات الأداء والنية السلوكية، وكذلك العلاقة بين توقعات الجهد والنية السلوكية. كما أثّر عامل الخبرة في تعديل العلاقة بين توقعات الجهد والنية السلوكية.

الآثار العملية: تقدم هذه الدراسة رؤى مهمة لتطوير وتنفيذ تدخلات فعالة في مجال الصحة المحمولة في مصر، إذ تحدد العوامل التي تؤثر على استخدام هذه التطبيقات بين المستهلكين في مجال الرعاية الصحية، مما يساعد الممارسين في تحسين الوصول إلى الرعاية الصحية ونتائجها، من خلال تصميم حلول صحية رقمية أكثر ملاءمة لاحتياجات وتفضيلات المرضى، مما يؤدي إلى زيادة التبني والاستخدام.

الأصالة/القيمة: تُعد هذه الدراسة الأولى من نوعها التي تقدم تحليلاً شاملاً لتبني تطبيقات الصحة المحمولة في مصر استنادًا إلى نموذج نظري موحد، وتوفر توصيات

قائمة على الأدلة لتطبيق التكنولوجيا الصحية في الأسواق الناشئة المشابهة، والتي تضم فئات سكانية شابة ومواكبة للتحول الرقمي.

الكلمات المفتاحية: النوايا السلوكية، مستهلكو الرعاية الصحية، التكنولوجيا الصحية، التطبيقات المحمولة، النموذج النظري الموحد.

1. Introduction

The contemporary era has witnessed an unprecedented transformation in healthcare delivery through the integration of digital technologies. Mobile health (mHealth) applications have emerged as one of the most significant innovations in healthcare digitalization, representing a paradigm shift from traditional healthcare models to patient-centered, technology-enabled care. These applications leverage smartphones and mobile devices to provide comprehensive health services, including disease surveillance, treatment support, chronic disease management, remote patient monitoring, and preventive care education (Franklin, 2021; Goel and Taneja, 2023). The global mHealth market has experienced remarkable growth, reaching $50.7 billion in 2021 with projections indicating expansion to $149 billion by 2028, while over 350,000 mHealth applications are currently available across major app stores (Grand View, 2022). The regulated mHealth application market demonstrates substantial future potential, with forecasts predicting sales of $15.6 billion by 2033, highlighting the technology's critical role in modern healthcare infrastructure.

Egypt presents a unique and compelling case for mHealth technology adoption, characterized by substantial digital infrastructure and user engagement alongside significant healthcare challenges. The country's population of 111.8 million as of 2023 demonstrates robust digital presence, with 72% internet penetration and 94% smartphone ownership according to CAPMAS (2023). Egyptian users exhibit exceptional digital engagement, spending an average of 7 hours and 41 minutes online daily, significantly exceeding global averages. This digital foundation provides an ideal environment for mHealth technology deployment. The Egyptian government has actively promoted digital health transformation through the introduction of a nationwide healthcare coverage initiative in 2021, supporting private healthcare providers and mobile health startups, which resulted in the emergence of approximately 100 healthcare startups within the country (Raven, 2021). Egypt's healthcare system faces increasing demands due to treatment advancements and limited resources, making mHealth technology essential for addressing these systemic challenges (Osman et al., 2023).

Despite Egypt's substantial digital infrastructure and governmental support for digital health initiatives, the country faces a paradoxical situation where mHealth technology adoption remains surprisingly limited among patients. This phenomenon is particularly puzzling given the extensive smartphone penetration and high levels of digital engagement among the Egyptian population. Early research by Mansour (2017) revealed that only 34% of Egyptian users had previous experience with mHealth applications, indicating persistent barriers to adoption. The mHealth sector in Egypt remains in its early developmental stages, with adoption rates slowing following the end of the COVID-19 pandemic despite the technology's proven benefits during the health crisis (Osman et al., 2023; Refaat, 2023).

The primary aim of this study is to investigate the mobile health factors that influence technology acceptance among Egyptian patients, providing comprehensive insights into the determinants of mHealth adoption in this unique cultural and technological context. Accordingly, four fundamental research questions are sought to be addressed to understand mHealth technology acceptance among Egyptian patients. First, do Egyptian patients accept mHealth applications to support their practical health needs, and what factors influence their acceptance levels? Second, what specific motivational factors lead Egyptian patients to embrace and utilize mHealth applications in their healthcare management? Third, what barriers and challenges do Egyptian patients face when considering or attempting to use mHealth applications, and how do these barriers differ across demographic groups? Fourth, what are the most significant positive mHealth factors that influence technology acceptance among Egyptian patients, and how can these factors be leveraged to improve adoption rates? These questions form the foundation for a comprehensive investigation into the complex dynamics of mHealth technology acceptance in Egypt. This study is structured into section 2 which contains literature review, while section 3 contains the methodology, section 4 contains statistical analysis. Finally, section 5 will be the conclusion.

2. Literature review

Mobile Smartphone Applications (also known as apps) are software applications developed specifically for use on small, wireless computing devices. When a mobile app is unlocked for usage by the individual, the app interconnects with the device's operating system and other built-in software components, opening and using the device's hardware and services, such as the camera and internet connection; the app uses this information to offer its specific functions and services to the individual (Anderson and Taylor, 2021). According to Statista (2024), with over 6.3 billion smartphone users across the world, the mobile app industry is prosperous, becoming popular among individuals for various consumption products and services. Castillo-Valdez et al (2024) explain that app usage and smartphone penetration are growing steadily, without slowing down in the foreseeable future.

To access a certain app, individuals need to download and install them via app stores on the mobile phone. Mobile apps provide individuals with a convenient way to access information, entertainment, products, and services on their mobile phones; it can be used to access information, such as news and weather updates, and to perform errands, such as online shopping and booking travel. Mobile apps can also enhance productivity and streamline communication. There are different varieties of apps, which include games, social media platforms, emailing services, banking apps, etc. (Martin and Lopez, 2021). A common app that is used by many individuals are health apps, especially during the start of covid-19 pandemic (Nguyen and Patel, 2020).

The number of smartphone mobile users has exploded in recent years. In 2023, there were almost 7 billion smartphone users worldwide, and this number is expected to keep growing to reach over 7.7 billion by 2028 (Petroc Taylor, 2024). These devices rely on software called apps to function. Apps are available for download from app stores like Google Play Store and Apple App Store. The number of available apps has also skyrocketed. By August 2024, the Google Play Store had around 2.3 million apps for android operating system, while Apple's App Store had about 2 million apps for iOS. In 2023, people downloaded a total of 257 billion mobile apps, and this trend is expected to continue, with app revenue reaching over $613 billion by 2025 (Ceci, 2024).

According to scholars and practitioners, there are three types of apps that are developed by businesses in the field: Native app, hybrid app, and web apps (Gunawardhana, 2021). A native app is a mobile app that is developed for one particular operating system (iOS or Android). They are coded and executed in the machine language and are only developed to one platform at a time. That is why Native apps have better performance than others. These apps can work and take full advantage of the device's features like vibration, camera, Bluetooth, and GPS; this means that the app lives on the mobile device, storing the data it needs to operate and integrating with mobile functions (e.g., camera or microphone) (Käld, 2021).

Hybrid apps, like Instagram and Gmail are technically web apps, but they can behave and act like native apps. They run within an app-embedded web browser; nevertheless, these apps can function on multiple platforms and operating systems such as iOS or Android with one codebase; with hybrid apps, businesses build one version of the product (Ceci, 2024). Web apps run in a web browser so to allow users to interact with the content and perform specific tasks online. They usually have less device access, a harder time displaying a native UI appearance, and poorer performance; however, they are easier to implement and cheaper to develop and maintain. This kind of app often includes functionalities, such as data processing, user authentication and real-time updates. Examples include online banking systems, social media platforms and e-commerce sites (Käld, 2021). Native applications are currently the best for developers, companies and organizations that are shifting to mobile application world because performance and user experience are more efficient and better in Native Applications than in Hybrid Applications (Choudhary RA, 2020). Native apps are optimal. They provide better user experience than Hybrid apps. However, performances, user experiences, and technical capabilities of Hybrid apps are closer enough to Native ones. In fact, Hybrid apps are considered advanced version and viable alternative of Native apps (Gunawardhana, 2021).

2.1 Mobile Connection and App Usage in Egypt

Contemporary market research shows that in January 2024, total population of Egypt were 113.6 million, increased by 1.7 million (+1.6%) year-on-year (y-o-y) with 50.6% are male population. 43.2% were living in urban centers while 56.8% were in rural areas (Digital 2024: Egypt). With a median age of 24.3, significantly younger than the global average of 30.6, Egypt boasts a youthful population that fuels a vibrant and evolving digital landscape. Smartphones are the primary means of digital engagement (Egyptians and Digital, 2024).

The number of internet users in Egypt stood at 82.1 million, with penetration rate 72.2%. Active cellular mobile connections were 110.5 million, equivalent to 97.3% of the total population. 27.8% of the population (31.58 million) stayed offline at the start of 2024. As indicated by Kepios analysis, internet users in Egypt increases by 1.6% (1.3 million) from January 2023 to January 2024 (Digital 2024: Egypt). Ookla’s data indicates that the median mobile internet connection speed in Egypt decreased by 0.06

Mbps (-0.3%) in the last year while fixed internet connection speeds increased by 18.59 Mbps (+40.5 percent) (Digital 2024: Egypt). Ookla states that Egypt Ranks 1st in Africa for Fixed Broadband Speed, 3rd on Offshore BPO Confidence Index 2023 and climbs 16 spots on GSMA Mobile Connectivity Index, Moving to ‘Advanced’ Category (MCIT Yearbook, 2023)

At the start of 2024, data from GSMA Intelligence (2024) reveals that number of cellular mobile connections in Egypt were 110.5 million which is equivalent to 97.3% of Egypt total population with increase rate of 4.1% (y-o-y), noting that many people make use of more than one cellular mobile connections (Digital 2024: Egypt). Due to the National Telecom Regulatory Authority (NTRA) efforts, Egypt achieved an overall score of 65.2 on the GSMA Mobile Connectivity Index and stands as the 7th most improved in the Middle East and Africa for the year 2023 climbing 16 Spots on GSMA Mobile Connectivity Index, Moving to ‘Advanced’ Category (MCIT Yearbook, 2023).

When it comes to mobile apps usage in Egypt, 96% of internet users among Egyptians primarily accessing the web through mobile devices, it's clear that smartphones have become the dominant platform for online engagement. This trend is further solidified by the fact that mobile devices now account for a substantial 55.8% of daily internet time, emphasizing their central role in Egyptians' digital lives. The data reveals that Egyptians exhibit a high level of internet usage, dedicating an impressive 7 hours and 55 minutes daily to online activities. This surpasses global average of 6 hours and 40 minutes, indicating strong digital engagement within the country (Egyptians and Digital, 2024).

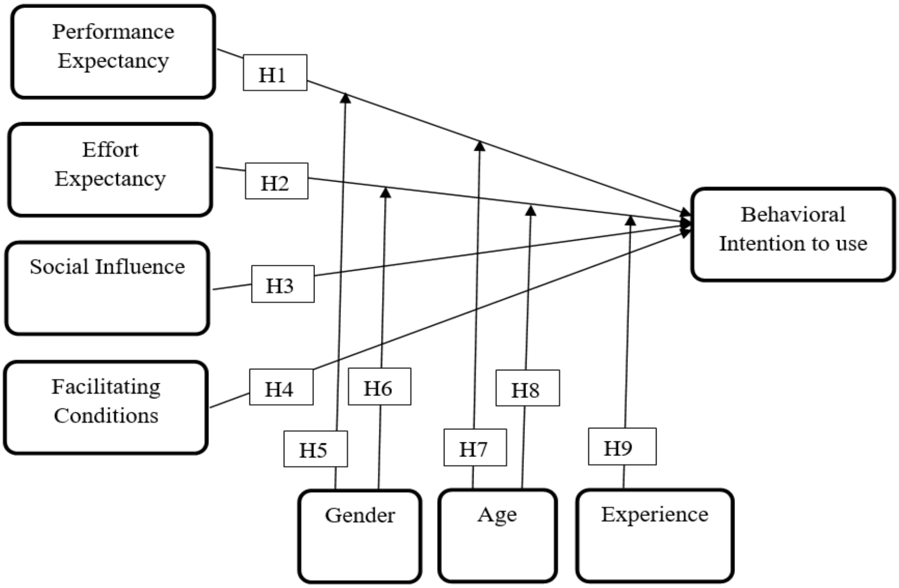
Research show that 45.15 million individuals aged 18 and above actively used social media platforms, representing a substantial 64.1% of the adult population, with 55.4% of all internet users in Egypt, regardless of age, engaged with at least one social media platform, while women comprised 38.6% of social media users, men held a significant majority at 61.4% (Digital 2024: Egypt). Indicating that Egypt still has a significant gender gap in social medica usage, while women constitute 49.8% of the population, they represent only 38.6% of social media users in 2023, resulting in a significant 10.8% gender gap. This social media gender gap can be correlated to the difference in literacy rates. With adult female literacy at 69% compared to 80% for men, a clear correlation emerges (Egyptians and Digital, 2024).

In the context of healthcare, research show that Egypt is actively embracing digital health technologies to modernize its healthcare system. The government is encouraging this transformation through initiatives like telemedicine, electronic health records, and mobile health applications. This has resulted in rise of health-tech startups, like Chefaa, Vezeeta, and D-Kimia, leading the charge in areas such as online pharmacy, appointment scheduling, and teleconsultations. These innovative start-ups are playing a crucial role in improving healthcare accessibility, efficiency, and patient outcomes across the country (Vidhi Upadhyay, 2023).

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Many models have been emerged in the literature to explain why and how individuals accept various technologies found in the market that can be used to improve overall lifestyle and efficiency (Deng Honglin et al, 2024). Nevertheless, the Unified Theory of Acceptance and Use of Technology (UTAUT) is used in this current study as it combines elements from eight different models that are prominent and significant in the literature regarding technology acceptance; the Theory of Reasoned Action, the Technology Acceptance Model, the Motivational Model, the Theory of Planned Behavior, the Model of PC Utilization, Innovation Diffusion Theory, and Social Cognitive Theory (Venkatesh et al., 2012). UTAUT explains how individuals adopt and use new technologies. UTAUT proposes that four key factors – performance expectancy, effort expectancy, social influence, and facilitating conditions – directly influence behavioral intention to use a technology, which in turn impacts actual usage as shown in figure 1 (Bettiga et al., 2020). This model is the bases for this study as the research seeks to investigate performance expectancy, effort expectancy, social influence, and facilitating condition on mobile health (mHealth) application adoption among Egyptian healthcare consumers. The research seeks to identify the key predictors of behavioral intentions to mHealth apps and explore how demographic factors moderate the relations. The following paragraphs explain each variable found in the model.

Figure 1: The Unified Theory of Acceptance and Use of Technology (UTAUT)



Source: Venkatesh et al. (2023)

Scholars have shown that performance expectancy leads to individuals to believe using a system will enhance their performance, is a key determinant in technology acceptance models (Venkatesh et al., 2012). Recent research underscores its significance in mHealth adoption (Bettiga et al., 2020).

According to a study by Teresa Mescher et al (2024) and Joo et al. (2023), users are more likely to engage with mHealth applications if they perceive them as effective in managing health conditions, providing real-time monitoring, and improving access to medical care. Furthermore, another study highlights that mHealth apps demonstrating high efficacy in diagnosing and managing diseases, such as malaria detection using AI-based applications, significantly enhance users' behavioral intention (Deng Honglin et al, 2024). Accordingly, this study developed Hypothesis One.

Hypothesis 1: there is a positive significant relation between performance expectancy and behavioral intention to use of mHealth.

According to scholars, effort expectancy impacts consumer behavior and that perceived ease of use of a technology, plays a crucial role in mHealth adoption (Venkatesh et al., 2012; Joo et al., 2023). A study on user willingness to adopt mHealth applications emphasizes that a user-friendly interface, minimal learning curve, and intuitive design increase the likelihood of adoption (Shaojing Fan et al, 2024). Moreover, another study found that applications requiring extensive effort to navigate or understand deter users, particularly among older populations who may have lower technological literacy (Slade et al., 2024). The Nature study on malaria detection tools also corroborates this, indicating that rapid and easy-to-use diagnostic applications improve engagement, as users prefer straightforward solutions over complex ones (Deng Honglin et al, 2024). Accordingly, this study developed Hypothesis Two.

Hypothesis 2: there is a positive significant relation between effort expectancy and behavioral intention to use of mHealth

Social influence on technology acceptance behavior has been acknowledged to impact consumers in encouraging the use of various technologies (Bagozzi et al., 2024). Holden et al. (2023) claim that subjective norm has been dominantly used to capture the essence of social influence. According to Venkatesh et al. (2023), social influence is the extent to which individuals perceive that significant others believe they should use a particular technology, has been widely studied in technology acceptance research. Shaojing Fan et al (2024) found that social influence plays a pivotal role in the adoption of mHealth applications, particularly among individuals who rely on recommendations from healthcare professionals, family, or peer networks. Additionally, Teresa Mescher et al (2024) highlights that social media endorsements and online health communities significantly contribute to mHealth adoption, as users tend to trust applications with positive reviews and widespread usage within their social circles (Teresa Mescher et al, 2024). Accordingly, this study developed Hypothesis Three.

Hypothesis 3: there is a positive significant relation between social influence and behavioral intention to use of mHealth

Benbasat and Barki (2023) explain that it is important that facilitating conditions exist so to allow individuals to adopt technology; it is significant that individuals believe that they have support from the organization, which includes technical support that are necessary to sustain the use of the system. According to Venkatesh et al. (2012), facilitating conditions refer to the availability of resources and support that make using a technology easier; to facilitate means to make something easier. Teresa Mescher et al (2024) emphasizes that regulatory approvals, data security measures, and healthcare provider endorsements serve as crucial facilitating conditions that enhance trust in mHealth applications. Furthermore, Deng Honglin et al (2024) suggests that infrastructure factors, such as mobile connectivity and integration with existing healthcare systems, impact users' willingness to adopt mHealth solutions. Shaojing Fan et al (2024) further highlights that individuals with greater access to technological resources and digital health literacy are more inclined to use mHealth apps. Accordingly, this study developed Hypothesis Four.

Hypothesis 4: there is a positive significant relation between facilitating condition and behavioral intention to use of mHealth

Shaojing Fan et al (2024) claim that demographic factors, including age, gender, education level, and digital literacy, significantly influence mHealth adoption. Shaojing Fan et al (2024) found that younger individuals, particularly those familiar with digital technologies, exhibit higher adoption rates compared to older populations. Gender differences were also noted, with women being more likely to use mHealth applications for health tracking and wellness management. Additionally, Teresa Mescher et al (2024) reports that individuals with chronic conditions or frequent healthcare needs demonstrate a greater behavioral intention to use mHealth apps due to their potential benefits in continuous health monitoring. Deng Honglin et al (2024) highlights regional disparities, noting that individuals in areas with limited healthcare access show a stronger inclination towards using mHealth applications as a primary means of receiving healthcare support.

3. Research Methodology

The research philosophy provides the framework for how the view and the approach of the research process. The assumptions underlying the research philosophy are crucial because they influence which data to be considered important and how to interpret its meaning (Saunders, 2023). This study used the Pragmatism Research Philosophy, for a pragmatist, research starts with a problem and aims to contribute practical solutions that inform future practice. Pragmatism prioritizes the research problem and question, recognizing multiple perspectives and methods. In pragmatism, the research problem and question drive the choice of research design and methodology. Pragmatists acknowledge the diversity of perspectives and the potential for multiple realities (Kelemen and Rumens 2011).

In this study, quantitative research was applied as the investigation approach. Quantitative research strategy relies on numerical data and used quantification in collection and analysis of data to investigate research questions. It employs a deductive approach to study the relationship between theory and research. This approach involves collecting and analyzing numerical data, often through surveys, experiments, or statistical analysis. By quantifying variables and employing statistical techniques, researchers can identify patterns, test hypotheses, and make generalizations about a population. The findings from quantitative research are typically presented in a clear and concise manner, facilitating comparison and interpretation (Bryman, 2022). In this study, deductive approach was used; the research starts with a theoretical framework (theory) to formulate specific hypotheses to be tested. Data is then collected and analyzed to either support or refute these hypotheses.

This study is conducted in a non-contrived setting as the people that are selected to participate in this study are requested to participate whenever it is convenient for them. The researcher distributes the survey to the studied target population without interfering with the normal activities in the natural setting. The researcher interference has been minimal (Saunders, 2023). In this study, the researcher plans to distribute questionnaires in the natural environment in which events occur normally without any interference from his side. Data was gathered from January 2024 till June 2025, following a cross sectional framework. The cross-sectional or short-term study involves the collection of data at a specific point of time; is conducted where data is gathered only once.

The population of focus is the Egyptian patients and health care practitioners, and the sampling technique chosen is River sampling (Bryan, 2022). River sampling is a method of online survey recruitment where respondents are intercepted while browsing the internet. It involves placing survey invitations (like banners or ads) on websites, and when users click on them, they are directed to a survey, potentially undergoing a screening process first. This approach is also known as intercept sampling or real-time sampling

The data collection is through an online questionnaire that was placed on google form. The questionnaire was placed on various social media pages and websites related to hospitals and clinics that offer mobile health services. The Inclusion criteria is: Egyptian patients and healthcare practitioners living in Great Cairo or Alexandria who agree to voluntarily participate. No age or gender limitation as the effect of both as moderating factors is within the scope of this research. Exclusion criteria: Non-Egyptians because their original culture, environment and education might have a great effect on their use of technology. Unwilling individuals to participate or involuntarily use the system.

The questionnaires were offered in both English and Arabic languages, the first half of the questionnaire consists of demographic information of the sample to evaluate the moderating variables (gender, age, and mHealth using experience). The second half of the questionnaire evaluate the effect of independent variables and indicators on the dependent variable and indictors using the 5-point Likert-type scale questions ranging from 1= strongly disagree to 5= strongly agree. These scales were taken from prior studies. For example, Performance expectancy (PE) and Effort expectancy (EE) were taken from the study of Khan et al. (2019); Social influence (SI) was taken from the study of Essam Mansour (2017); Facilitating conditions (FC) and Behavioral Intention to Use (BIU) were taken from the study of (Khan et al., 2019); and the gender questions were inspired by the study of Essam Mansour (2017). A pretest was conducted among 50 respondents to confirm the validity and the reliability of the study.

Once the data was collected, the researcher used the SPSS (Statistical Package for Social Sciences) as well as SEM (Structural Equation modelling) statistical software platform, applying statistical techniques such as descriptive analysis, correlation analysis, and regression analysis.

4. Quantitative Results

405 respondents were analyzed in this study. The participants in this study came from different socio-demographic as shown in table 1. The sample shows a moderate male predominance, with 225 male respondents comprising 55.6% of the total sample, while 180 female respondents represent 44.4%. This distribution indicates a relatively balanced gender representation with a slight skew toward male participants. The difference of approximately 11 percentage points suggests that while both genders are well-represented, males were somewhat more likely to participate in this mHealth apps research, which could reflect different engagement patterns with health technology or survey participation rates between genders.

The generational breakdown reveals a striking concentration among Millennials, who constitute the overwhelming majority at 333 respondents or 82.2% of the sample. Generation X represents the second-largest group with 56 respondents (13.8%), while Generation Z accounts for only 13 respondents (3.2%). Baby Boomers show minimal representation with just 3 respondents (0.7%). This distribution suggests that the study predominantly captures the perspectives of Millennials, who are typically in their late 20s to early 40s and represent a generation that has grown up with or adapted to digital technology. The limited representation of Generation Z is somewhat surprising given their digital nativity, while the minimal Baby Boomer participation may reflect lower adoption rates of mHealth technologies among older adults.

The experience levels among respondents show a fairly even distribution across the middle categories, with Advanced users slightly leading at 132 respondents (32.6%), followed closely by Intermediate users at 130 respondents (32.1%). Novice users comprise 104 respondents (25.7%), while Expert users represent the smallest group with 39 respondents (9.6%). This distribution indicates that the majority of participants have substantial experience with mHealth applications, with nearly 75% falling into the Intermediate, Advanced, or Expert categories. The relatively small proportion of Expert users suggests that while many respondents are comfortable with mHealth apps, true expertise remains less common, possibly reflecting the complexity of fully mastering these technologies or the diverse range of available applications.

Table (1): Demographic Characteristics

Aspect	Classification	Frequency	Percentage
Gender	Male	225	55.6%
	Female	180	44.4%
Total		405	100%
Generation Age	Millennials	333	82.2%
	Gen Z	13	3.2%
	Gen X	56	13.8%
	Baby Boomers	3	0.7%
Total		405	100%
Experience rate in using mHealth apps	An Intermediate user	130	32.1%
	An Expert user	39	9.6%
	An Advanced user	132	32.6%
	A Novice user	104	25.7%
Total		405	100%

The multicollinearity between the independent variables was the first measure that was done by the researcher before the significance of the relationships in the structural model could be tested. In order to find out whether there was any multicollinearity between the independent variables used in this research, the variance inflation factor (VIF) was used to check so that there was none correlated excessively thus leading to distortion of the model parameters as was reported by Kleinbaum and others (1988). In the regression analysis as per the results, the value of VIF was between 1.000 and 2.879 as seen in Table 4 which implied much lesser than 10. On the basis of (Hair et al., 2014), indicators of multicollinearity can be observed when VIF indicator exceeds 5. The issues of multicollinearity are not present in the structural model. The outcome is shown in table 2.

The score of the internal consistency of a scale as measured by Cronbach alpha is acceptable when greater than 0.7, showing good reliability of 0.8, and excellent reliability of 0.9 and above (Lee & Joseph, 2008). Behavioral Intention to use (0.898) and Performance Expectancy (0.883) are good measures in this study. Effort Expectancy (0.837) also portrays a good reliability since it is above 0.8 level. Both Facilitating Conditions (0.765) and Social Influence (0.764) have internal consistency scores that are within the acceptable levels of 0.7 and above representing. The reliability of all items in a measurement model is acceptable and proves that all the items in a scale are reliable in finding appropriate constructs.

Composite reliability evalautes relatedness or relationship of the internal consistency of a construct and values that are beyond 0.7 are accepted whereas the values that are higher than 0.8 show reliability (Lee & Joseph, 2008). These findings reveal that Behavioral Intention to use (0.936) has a high reliability of a measure of 0.936, and it visualizes that more than 0.9. Both, Performance Expectancy (0.919) and Effort Expectancy (0.891) are highly reliable with a reliability mark well above 0.8. Facilitating Conditions (0.847) and Social Influence (0.841) have also good reliability exceeding the acceptable 0.7 value. The measurement model is showing adequate internal consistency because all the constructs have a high composite reliability of more than 0.7 and therefore the scale items are showing reliability in measurement of the intended constructs (Lee and Joseph, 2008).

Validity refers to the extent to which a measurement scale accurately measures the construct it is intended to measure. There are two primary types of validity: content validity and construct validity. Within construct validity, there are two subtypes: convergent validity and discriminant validity. Content validity ensures that the measurement tool comprehensively covers all aspects of the construct, meaning it includes all relevant dimensions of the concept being measured. Construct validity uses the extent to which the tool measures the given theoretical concept. Construct validity has two subtypes, convergent validity, which tests the extent, to which items constructed to measure a construct are highly interconnected, and discriminant validity, which tests the extent, to which items constructed to measure different constructs are interconnected to each other and are not closely related. The combined version of these versions of validity is useful in ensuring that the construct studied is well represented by the measurement.

Table (2) Combined VIF and Reliability Analysis- Measurement Model Indicators

	Variable	VIF	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Age		1.000	1.000	1.000	1.000
Behavioral Intention to use	BI1	2.656	0.898	0.936	0.830
	BI2	2.879			
	BI3	2.753			
Effort Expectancy	EE1	2.209	0.837	0.891	0.672
	EE2	2.428			
	EE3	1.571			
	EE4	1.803			
Effort Expectancy * Gender		1.000	1.000	1.000	1.000
Experience		1.000	1.000	1.000	1.000
Facilitating Conditions	FC1	1.345	0.765	0.847	0.582
	FC2	1.463			
	FC3	1.536			
	FC4	1.652			
Gender		1.000	1.000	1.000	1.000
GenderxEE		1.000	1.000	1.000	1.000
GenderxPE		1.000	1.000	1.000	1.000
Performance Expectancy	PE1	2.322	0.883	0.919	0.741
	PE2	2.548			
	PE3	2.096			
	PE4	2.242			
Performance Expectancy * Gender		1.000	1.000	1.000	1.000
Social Influence	SI1	1.398	0.764	0.841	0.517
	SI2	1.433			
	SI3	1.798			
	SI4	1.247			
	SI5	1.750			

Convergent validity diagnoses how likely that all the items of particular measurement are related and measure one unobserved variable (Joseph F. Hair Jr. et al., 2014). The convergent validity was determined with a typical measure of convergent validity, which is the average variance extracted (AVE) in PLS-SEM (Alam et al., 2024). The findings indicate that Performance Expectancy has the best AVE (0.741) as compared to Behavioral Intention to use (0.830), Effort Expectancy (0.672), Facilitating Conditions (0.582), and Social influence (0.517). The values of AVE are all higher than the recommended value of 0.50 by Alam et al. (2024), and its values are between 0.517 to 0.830, which indicates consistency of measures and validates the convergent validity as well. Discriminant validity is very much the extent to which a construct is really differentiated about another construct in the actual and conceptualization sense and also in the measurement sense. They stress that the determination of discriminant validity helps make sure that a construct is one of a kind and more phenomena are covered by it than by other constructs in this model (Clay M. Voorhees et al., 2016). The discriminant validity was evaluated against Fornelllarcker criterion and heterotrait monotrait (HTMT) ratio method in the evaluation of the strength of validity. The analysis is shown in table 3

Table (3): HTMT ratio

	Age	Behavioral Intention to use	Effort Expectancy	Experience	Facilitating Conditions	Gender	GenderxEE	GenderxPE	Performance Expectancy
Age									
Behavioral Intention to use	0.023								
Effort Expectancy	0.175	0.512							
Experience	0.003	0.271	0.237						
Facilitating Conditions	0.099	0.428	0.552	0.146					
Gender	0.052	0.025	0.034	0.059	0.049				
GenderxEE	0.099	0.059	0.139	0.044	0.077	0.000			
GenderxPE	0.078	0.164	0.032	0.051	0.201	0.003	0.483		
Performance Expectancy	0.026	0.740	0.544	0.277	0.489	0.022	0.033	0.218	
Social Influence	0.194	0.434	0.560	0.144	0.366	0.114	0.092	0.145	0.444

The predictability of structural model was inferred based on the R squared values, which reflects the number of variances explained by the dependent constructs. The R 2 of the Behavioral Intention to use was 48.2, which means that 48.2 percent of its variability is accounted by the predictors of the model. It can be interpreted that the dependent variables have moderate to high predictive relevance to the model, and the adjusted R 2 values (0.482 in Behavioral Intention to use) supports its strength (Table 4).

Table (4): R^2 and Adjusted R^2 Values

Variables	R-square	R-square adjusted
Behavioral Intention to use	0.494	0.482

Model fit is evaluated using two models such as the saturated model and the estimated model. The saturated model presupposes that all constructs are maximally interconnected being a baseline indicator of fit, which is unconstrained. The estimated model on the other hand indicates the relationships that are hypothesized and will give an indication of how good the proposed structure is compared to the observed data. In this study, three major indicators were used in order to determine the fitness of the model: these are the Standardized Root Mean Square Residual (SRMR), the Chi-square statistic, and the Normed Fit Index (NFI). All these indicators evaluate the fit of the preliminary structural model and observed measures.

The Normed Fit Index (NFI) demonstrates strong model fit, with identical values of 0.814 for both the Saturated Model and the Estimated Model. These values exceed the commonly accepted threshold of 0.80 and approach the more stringent threshold of 0.90 recommended in some literature. The consistent NFI values across both models provide robust evidence of adequate fit for the hypothesized model, particularly suitable for this research context (see Table 5).

Table (5): Model Fit Summary (Saturated and Estimated Models)

	Saturated Model	Estimated Model
SRMR	0.058	0.058
d_ULS	0.938	0.938
d_G	0.318	0.319
Chi-Square	773.819	775.539
NFI	0.814	0.814

Table (6) presents the results of hypothesis testing, showcasing the path coefficients, T-statistics, and p-values, which are essential for evaluating the strength and significance of the relationships between the constructs in this study. The results of the hypothesis testing show that five out of six hypotheses were supported. Specifically, animosity has a significant positive effect on both attitude and boycott intention. Attitude also mediates the relationship between animosity and boycott intention. Xenocentrism was found to moderate the relationship between animosity and boycott intention. Surprisingly, moderation is positive, suggesting that xenocentric tendencies strengthen the effect of animosity on boycott intentions. Also, the hypothesized moderating effects of materialism and post-materialism on the relationship between attitude and boycott intention were not supported, as the results showed no significant effect.

Table (6): Hypotheses Testing Results

Hypothesis		Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H 1	Performance Expectancy -> Behavioral Intention to use	0.497	0.495	0.051	9.780	0.000
H 2	Effort Expectancy -> Behavioral Intention to use	0.151	0.145	0.053	2.865	0.004
H 3	Social Influence -> Behavioral Intention to use	0.096	0.103	0.044	2.165	0.031
H 4	Facilitating Conditions -> Behavioral Intention to use	0.064	0.069	0.054	1.177	0.240
H 5	GenderxPE -> Behavioral Intention to use	-0.093	-0.094	0.047	1.997	0.046
H 6	GenderxEE -> Behavioral Intention to use	0.131	0.128	0.042	3.139	0.002
H 7	AgexPE -> Behavioral Intention to use	-0.040	-0.025	0.068	0.591	0.554
H 8	AgexEE -> Behavioral Intention to use	0.040	0.040	0.047	0.850	0.396
H 9	ExperiancexEE -> Behavioral Intention to use	-0.083	-0.081	0.035	2.355	0.019

4.1 Research Discussion

This study utilized the structural equation modelling in investigating the factors that have implications in behavior intentions to use a technology system. Analysis established an acceptable level of the model reliability and validity and all constructs indicated an acceptable level of Cronbach alpha (0.764 to 0.898), composite reliability values which were above 0.7 and average variance extracted values above 0.50. The structural model showed acceptable values of good fit (SRMR = 0.058, NFI = 0.814) and accounted 48.2 percent of variance in behavioral intention to use.

Hypothesis testing indicated that six of nine hypotheses were supported; the relationships between Performance Expectancy (indirect coefficient = 0.497, $p < 0.001$), Effort Expectancy (indirect coefficient = 0.151, $p < 0.01$), and Social Influence (indirect coefficient = 0.096, $p < 0.05$) and behavioral intention were all significant and positive, and Gender significantly moderated both the Performance Expectancy-behavioral intention (indirect coefficient = -0.093 Nonetheless, there was no significant direct effect of the Facilitating Conditions and also no significant moderated relationships by the Age factor, and this indicated that although performance expectation, ease of use, and social aspects led to the intention to fact in technologies, age-factor played less moderating role than gender and prior experience.

There are a number of methodological limitations, which limit the applicability and range of the findings of the study. The study used the cross-sectional design, which hinders the creation of the causal relationship between the UTAUT constructs and behavioral intention of using the mHealth apps. Also, the use of self-report in the study based on questionnaires is likely to create bias in responses, as the respondents are likely to provide their socially desirable behavior instead of their intended behavior. Although the structural equation modeling methodology is quite sound, it presents the assumption that the association between variables is linear and this does not seem to capture the dynamics of adoption of technology within the true healthcare environment.

There are reasons to give views to cultural and contextual limitations of such a study as well. The research was led only in the area of the Egyptian healthcare system and therefore, the findings could not be transposed easily into any healthcare system, culture, and population level of digital literacy elsewhere in the Middle East or in the developing world. The study concentrated on the behavioral intention instead of behavioral practice, a discrepancy that occurs between claims and the actual adoption patterns. Moreover, by analyzing mHealth apps as an overarching category, the study might not take into consideration various capabilities and uses of various health apps, whether they are to track fitness or support chronic disease management and so on, they may have different associated factors of acceptance. The study is also limited in time, which, due to the dynamism of mobile health technology and the expectations of the user, it is unlikely that the results will respond to this change in post-pandemic times when a lot of digital health is adopted rapidly.

5. Conclusion and future study

This study investigates the factors influencing mobile health (mHealth) application adoption among Egyptian healthcare consumers, examining the applicability of the Unified

Theory of Acceptance and Use of Technology (UTAUT) model in an emerging digital health market context. The research aims to identify key predictors of behavioral intention to use mHealth apps and explore how demographic factors moderate these relationships, providing insights for healthcare technology implementation in developing markets. The research challenges conventional UTAUT applications by revealing context-specific patterns where basic technological infrastructure functions as a hygiene factor rather than a motivating factor.

A quantitative study was conducted using structural equation modeling (SEM) with SmartPLS to analyze data from 405 respondents. The predominantly Millennial sample (82.2%) with slight male predominance (55.6%) completed validated questionnaires measuring UTAUT constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention to Use. Moderation effects of gender, age, and experience were examined. Qualitative sentiment analysis and word cloud analysis supplemented quantitative findings to provide comprehensive understanding of healthcare professionals' perspectives on mHealth adoption barriers and facilitators. Performance Expectancy emerged as the strongest predictor of behavioral intention to use mHealth apps ($\beta = 0.497$, $p = 0.000$), followed by Effort Expectancy ($\beta = 0.151$, $p < 0.05$) and Social Influence ($\beta = 0.096$, $p < 0.05$). The model explained 48.2% of variance in behavioral intention. Contrary to

UTAUT predictions, Facilitating Conditions showed no significant effect on adoption intentions despite high infrastructure ratings. Gender significantly moderated relationships between Performance Expectancy and behavioral intention ($\beta = -0.093$, $p = 0.046$) and between Effort Expectancy and behavioral intention ($\beta = 0.131$, $p = 0.002$). Experience moderated the Effort Expectancy-behavioral intention relationship ($\beta = -0.083$, $p = 0.019$), while age showed no moderation effects. Sentiment analysis revealed 66.2% positive attitudes among healthcare professionals, with remaining concerns focusing on usability barriers and digital literacy gaps.

This research makes a substantial contribution to the existing body of knowledge in health informatics and technology acceptance theory by providing empirical evidence from an underrepresented Middle Eastern population. The study extends the application of established technology acceptance models to the mHealth domain within a developing country context, offering new insights into how cultural, social, and economic factors influence technology adoption patterns. The integration of digital literacy as a moderating variable represents a novel theoretical contribution that advances our understanding of the conditional effects that determine mHealth acceptance success or failure.

The methodological contributions of the research are also highly valuable since the work proves the successful use of the use of the advanced statistical information such as confirmatory factor analysis or structural equation modeling in the mHealth studies. The comparative approach where the covariance-based SEM is used in contrast with the variance-based PLS would advance us to consider the methodology which can be embraced by future researchers in order to choose the right analytical technique to use in subsequent researches of this nature. The study adds to the methods discussions on the benefits and drawbacks of various statistical methods used in health technology research especially in developing nations where the sample characteristics are not as they are in the West.

On the theoretical front, the study helps to build culture-sensitive theories of technology acceptance that would work in various world-contexts. The resulting critique is useful to challenge universalist conceptions regarding the adoption of technology and underline the role of context in the success of mHealth. The contribution of the research to the cross-cultural technology acceptance studies offers significant information to international scholars interested in learning how technologies of global health are able to be perceived and accepted in various cultures.

The study also adds to the body of knowledge in digital health equity and digital healthcare divide. The study fills gaps in theories about mHealth acceptance through the role of digital literacy as one of such moderators that should be considered when considering disparities in the use of healthcare technologies. This contribution is especially significant to health equity scientists and policy analysts who seek to make sure that when it comes to digital health innovation, it helps to decrease and not amplify health disparities in developing nations.

The feasibility of this research is that his work could easily be adopted in enhancing healthcare delivery in Egypt and other developing nations. The research findings can guide the healthcare administrators and managers to come up with evidence-based implementation plans of the mHealth technologies that consider the factor of patient acceptance and the level of digital literacy acquired by them. These insights will help healthcare organizations spend their resources in more efficient ways as it is clear which intervention will solve the most important barrier to the adoption of mHealth, as presented in the research.

This research can give technology firms and developers of mHealth good market intelligence and insights on users that they can use in product development and marketing. Development of the main acceptance factors allows developers to prioritize the use of features in the program and aspect of the design that has high likelihood of being attractive to the Egyptian patients. The results of the research can inform the design of user interface, content, and support system so that mHealth products become accessible and attractive to the target population of users.

The research outcomes can also be used in more targeted digital health strategies by healthcare policymakers and government representatives. The study offers evidence-based advice to policy-making in the setting of digital health infrastructure, training programs of the healthcare workers, and patient educational programs. The practical lessons could be used to develop national digital health plans and to guide in prioritizing those interventions, which are most likely to have a broad impact and sustainable uptake.

The findings of the research can be used by global health initiatives and international development organizations to enhance their work on mHealth programs by reflecting on their design and implementation better in the context of similar third world countries. These practical contributions go beyond Egypt and apply to the mHealth implementation strategies in Middle East and North Africa region, and other developing countries with comparable social economic and cultural backgrounds. It can be said that the article has given a framework on how to give a context-specific assessment and then implement mHealth interventions, which may end up increasing the success rate of other international digital health initiatives.

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