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An integrative research framework to investigate factors influencing citizen's intention to adopt e-health applications: post-COVID-19 perspective

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Abstract

Purpose – The use of e-health applications has remained popular during pandemic for medical treatments. Nevertheless, adoption of e-health applications among individuals is considerably low in post-COVID-19 world. To address this issue, the current research integrates three renowned theories, namely unified theory of acceptance and use of technology model, diffusion of innovation and DeLone and McLean model and investigates individual intention to adopt e-health application.

Design/methodology/approach – Research design is grounded in quantitative and cross-sectional methods and uses a survey questionnaire. Survey questionnaire is administered toward smartphone users. Overall, 238 valid responses were analyzed with structural equation modeling approach.

Findings – Results indicate that altogether performance expectancy, effort expectancy, information quality, system quality, service quality, facilitating condition and social influence explained substantial variance ($R^2 = 76.5\%$) in user intention to adopt e-health applications. Similarly, effect size analysis has revealed substantial impact of social influence on user intention to adopt e-health applications. Geiser and Stone's Q^2 analysis discloses that research model has substantial power to predict user intention to adopt e-health applications.

Practical implications – This study integrates three known information system models to investigate individual behavior toward adoption of e-health applications. In practice, it suggests that managers should pay attention in improving performance expectancy, social influence, facilitating condition, system quality, service

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quality and information quality which develop positive behavior and encourage smartphone users to adopt e-health applications.

Originality/value – This study is original as it integrates three models and investigates individual intention to adopt e-health applications. To the best of the author's knowledge, this is the first study to test the moderating impact of patient health value between user intention to adopt and actual use of e-health applications. It has established that compatibility and innovativeness are essential antecedents of performance and effort expectancy and hence make this research more unique and valuable.

Keywords Compatibility, Innovativeness, System quality, Social influence, Theories integration, E-health adoption, Patient health value

Paper type Research paper

1. Introduction

Over the past few decades, technology has changed traditional layout of health sector due to exponential increase in e-health applications (Ehn *et al.*, 2021). This dynamic change is due to the proliferation of technology and advance in fifth-generation cellular networks (Alam *et al.*, 2020). The term e-health applications is referred to digital healthcare service that enhance patient and practitioners overall experiences through Internet of Things (Ehn *et al.*, 2021). In a broader sense, e-health applications keep health record, promote healthy lifestyle, adherence to medication, self-monitoring and allow patients to dynamically exchange health informatics with healthcare practitioners (Alam *et al.*, 2020). More recently e-health applications have been recognized as a supportive technology tool in reducing COVID-19 pandemic and other chronic diseases (Wang *et al.*, 2022). Despite its several benefits to manage health related issues quickly and effectively adoption of e-health applications among individual is stagnant (Ehn *et al.*, 2021; Maramba *et al.*, 2019). According to Ehn *et al.* (2021), adoption of e-health applications is not only linked to technical development but it is a process of understanding user attitude and behavior toward acceptance and use of e-health technology. Although prior studies have investigated e-health adoption issues (Balapour *et al.*, 2019; Ehn *et al.*, 2021; Maramba *et al.*, 2019; Zobair *et al.*, 2019), however little is known about behavioral aspect of e-health technology users. Therefore, it is critical to identify which factors influence user intention to adopt e-health applications.

Maramba *et al.* (2019) posited that globally more than 325,000 e-health applications are available in all major app stores. However, these applications are incompatible with digital health solutions and hence remained unsuccessful (Greenhalgh *et al.*, 2017). Authors such as Elia *et al.* (2020) argue that policymakers and government bodies have failed to get people to use e-health applications. Therefore, current research integrates three known models, namely the unified theory of acceptance and use of technology (UTAUT), diffusion of innovation (DOI) model and DeLone and McLean information success (IS) model and examine individual behavior to adopt e-health applications. The DOI theory explains methods of technology diffusion that will be used in e-health information system (Attié and Meyer-Waarden, 2022). Therefore, the unified theory explains performance expectancy, social influence, effort expectancy and facilitating condition and evaluates user intention to adopt e-health information system (Alkhwaldi *et al.*, 2022; Pieters *et al.*, 2022; Venkatesh, 2022). Similarly, the DeLone and McLean IS model comprises system quality, information quality and services quality and examines individual intention to adopt e-health applications (Ibrahim *et al.*, 2023; Pushparaj *et al.*, 2022). Therefore, integration of these technology theories has disclosed unique findings which in turn help academic researchers and policymakers to understand factors influencing user intention to adopt e-health applications. In next section, literature review is conducted followed by research methodology, data analysis, discussion, research contributions, conclusion, research limitation and future research directions.

2. Literature review

2.1 Theories integration rational

Examining user behavior to adopt e-health system is critical and cannot be assessed with single theory-driven model (Song *et al.*, 2021). There are mutual consensuses among researchers that integrative research model has more strength to reveal scientific evidence (Cronin and George, 2020; Pal and Patra, 2021; Song *et al.*, 2021). Authors such as Song *et al.* (2021) had integrated attention interest and desire model with technology acceptance model (TAM) to investigate consumer behavior toward acceptance of food delivery applications. Similarly, Pal and Patra (2021) had integrated task technology fit theory and TAM model to understand student perception toward e-learning. However, current study integrates DOI theory, the UTAUT model and DeLone and McLean IS model to investigate individual intention to adopt e-health applications. There are several technology theories that discuss user intention to adopt information technology, for instance, TAM by Davis (1986) extended TAM by Venkatesh and Davis (2000) and task technology fit model by Goodhue and Thompson (1995). According to Venkatesh *et al.* (2003), a unified view is required to investigate user intention to adopt technology and hence the UTAUT model was introduced. The UTAUT model by Venkatesh *et al.* (2003) comprises factors such as social influence, performance expectancy, facilitating condition and effort expectancy. In current study, researcher has integrated UTAUT with DeLone and McLean success model that was introduced by Delone and McLean (2003). The Delone and McLean comprise factors such as system quality, service quality and information quality. As this study is talked about individual behavior to adopt e-health applications and therefore technology diffusion factors, namely innovation and compatibility were added in research model. Thus, individual intention to adopt e-health applications is assessed with the integration of UTATU model, DOI theory and DeLone and McLean model. The detail of these technology theories and conceptual linkage among exogenous and endogenous factors is proven in following sections.

2.2 Diffusion of innovation theory

DOI model explains that innovation is diffused through people over time (Rogers, 1962). Therefore, individual behavior toward adoption of technology could be examined through compatibility and innovativeness of the technology (Rogers, 1962). The term compatibility is known as the degree to which technology is perceived consistent with potential adopter needs, practices, values and past experience (Rogers, 2003). Prior studies have confirmed that compatibility is an important factor of technology diffusion and positively influence individual attitude to adopt technology (Leggott *et al.*, 2016; Rahi and Abd. Ghani, 2018). Authors such as Rahi and Abd. Ghani (2018) have proven positive impact of compatibility on performance expectancy and effort expectancy while using a specific technology. Prior studies had argued that e-health applications has multifaceted interface and therefore it must be compatible with user mind, belief and benefits (Haun *et al.*, 2020; Razmak *et al.*, 2018). Moving further innovation is the degree to which individual prefer to try out new technology and new idea to perform a task. According to Haun *et al.* (2020), individual willingness to try out new technology motivate individual to adopt new technology. Extending to this Rahi and Abd. Ghani (2018) asserted that user having intention to try out new things will perform better than others. Taking these arguments into account and backed by prior research work Haun *et al.* (2020); Razmak *et al.* (2018) following hypotheses are postulated:

H1. Compatibility positively relates to performance expectancy.

H2. Compatibility positively relates to patient effort expectancy.

H3. Innovativeness positively relates to performance expectancy.

H4. Innovativeness positively relates to effort expectancy.

2.3 *The UTAUT model and individual behavior to adopt e-health apps*

The unified theory comprises factors such as performance expectancy, effort expectancy, facilitating condition and social influence and investigates user intention to adopt e-health system (Baudier *et al.*, 2020; Rahi, 2022). The term performance expectancy is the extent to which user consider that use of e-health app will facilitate him/her in performing task and improve job performance (Baudier *et al.*, 2020). Therefore, effort expectancy is associated with degree of ease that user attain while using technology (Baudier *et al.*, 2020). Literature has long established that both effort expectancy and performance expectancy positively influence user intention to adopt technology (Alam *et al.*, 2020; Baudier *et al.*, 2020; Talukder *et al.*, 2020). According to Talukder *et al.* (2020), performance expectancy and effort expectancy positively affect user behavior to adopt wearable healthcare technology. Prior studies have shown that user wants stay connected with technologies that are convenient, advantageous and easy to use (Alam *et al.*, 2020; Gu *et al.*, 2021; Li *et al.*, 2019; Talukder *et al.*, 2020). Authors such as Li *et al.* (2019) have postulated that individual seem to be motivated and enthusiastic if they perceive that e-health applications are advantageous and improve job performance. Therefore, following hypotheses are proposed:

H5. Performance expectancy positively relates to individual intention to adopt e-health applications.

H6. Effort expectancy positively relates to individual intention to adopt e-health applications.

The UTAUT theory incorporates two other factors namely facilitating condition and social influence. Social influences are the extent wherein individual perceives that how important people opinion is how it influences individual behavior to adopt e-health applications (Gu *et al.*, 2021). Alam *et al.* (2020) posited that social circle including family and friends largely influence user behavior to adopt new technology. Prior studies have established that peer recommendation, suggestion and information could influence patient behavior to adopt new technology (Alam *et al.*, 2020; Gu *et al.*, 2021; Li *et al.*, 2019). In e-health context, Gu *et al.* (2021) have revealed that health conscious people give importance to friends opinion which in turn mold individual attitude to adopt e-health system. The term facilitating condition is seen as the degree to which patient perceives that infrastructure and relevant health devices are available for use of e-health applications (Alam *et al.*, 2020; Li *et al.*, 2019). Authors such as Li *et al.* (2019) stated that facilitating factor ensures that technology devices support to wireless networking system and capable to transmit ubiquitous health data into main health stream. Nevertheless, lack of access to technology infrastructure could negatively influence user attitude. Within information system studies have confirmed that technical support, adequate infrastructure and availability of sample devices increase consumer confidence and encourage to accept e-health applications (Alam *et al.*, 2020; Alkhwaldi, 2022; Gu *et al.*, 2021; Rahi *et al.*, 2021). Therefore, following hypotheses are postulated:

H7. Social influence positively relates to individual intention to adopt e-health applications.

H8. Facilitating condition positively relates to individual intention to adopt e-health applications.

2.4 DeLone and McLean model and intention to adopt e-health applications

The roots of DeLone and McLean model are connected with theory of communication invented by Shannon and Weaver (1949) and information system model by Mason (1978). Nevertheless, this model was extended by Delone and McLean (2003) to understand individual behavior to adopt and use of technology. The latest IS success model by Delone and McLean (2003) gives comprehensive view of IS characteristics and has gained researchers attention at large scale. The Delone and Mclean framework comprises factors such as service quality, system and information quality and have been widely studied in technology adoption setting (Çelik and Ayaz, 2022; Pour *et al.*, 2021; Rokhman *et al.*, 2022; Sebetci, 2018). Service quality directs to technology device wherein individual assess service quality through responsiveness, assurance and empathy (Rokhman *et al.*, 2022). Experts have revealed strong correlation between services quality and user intention to adopt new technology (Rahi and Abd. Ghani, 2019; Rokhman *et al.*, 2022; Shim and Jo, 2020).

The information quality is the extent to which user perceive that technology provides comprehensive, accurate, relevant, consistent and relevant information about e-health applications (Shim and Jo, 2020). Prior studies have revealed that information quality significantly influence user intention to adopt e-health system (Sebetci, 2018; Shim and Jo, 2020). The term system quality is the extent wherein user believes that system is flexible, feasible, reliable, portable and functional toward use of e-health applications (Al-Okaily *et al.*, 2023; Mahmud *et al.*, 2023; Oderanti *et al.*, 2021). According to Rokhman *et al.* (2022), system quality brings ease in technology use, improve process, enhance work efficiency and reduce cost. Prior studies have proven that system quality improves user satisfaction and positively influence user behavior to adopt e-health system (Oderanti *et al.*, 2021; Sebetci, 2018). Therefore, and backed by prior research work Oderanti *et al.* (2021); Sebetci (2018); Shim and Jo (2020) following hypotheses are assumed:

H9. Service quality positively relates to individual intention to adopt e-health applications.

H10. Information quality positively relates to individual intention to adopt e-health applications.

H11. System quality positively relates to individual intention to adopt e-health applications.

2.5 Patient health value

The adoption of e-health applications is associated with individual preferences that how they see health in daily lifestyle. According to Zhang *et al.* (2019), health value denotes to individual attention that they bestow on health and feels that health is essential for well-being and happiness. Earlier studies have indicated that health value regulate individual intention to accept or reject e-health applications (Deng *et al.*, 2015; Hertling *et al.*, 2022; Rahi *et al.*, 2021). More recently studies have claimed that individual with high level of perceived health value has shown incline to adopt of e-health applications (Alzougool, 2022; Badawy and Radovic, 2020; Nwagwu and Onyancha, 2022; Rahi, 2022; Tortorella *et al.*, 2022). Therefore, it is expected that individual with high perceived health value will use e-health applications to prevent diseases (Tortorella *et al.*, 2022). Consequently, current research adds a new dimension in e-health adoption framework as shown in Figure 1 and outlined patient health value (PRV) as moderating factor between patient intention to adopt and acceptance of e-health applications. Studies have conceptualized that health value preferences develop user positive attitude to adopt and use of e-health applications which in turn boost individual well-being and healthy lifestyle (Chakraborty

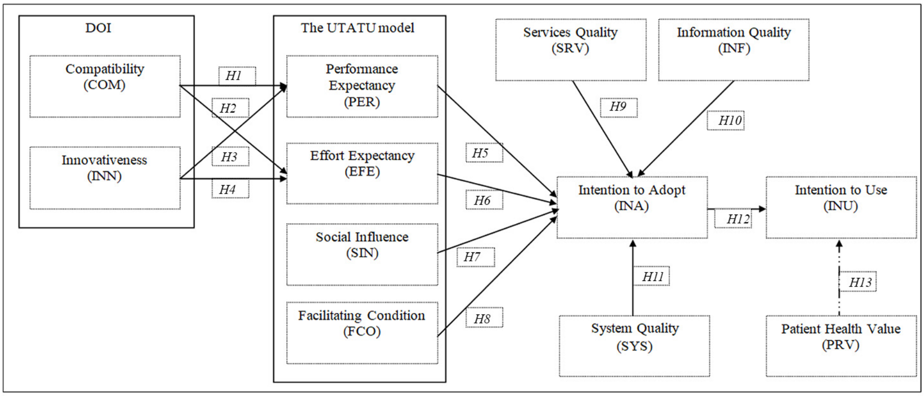


Figure 1.
Research framework

Source: Figure by authors

and Paul, 2022; Ray *et al.*, 2021; Wei *et al.*, 2021). Taking above arguments into account following hypotheses are assumed:

H12. Patient intention to adopt e-health applications positively relates to individual intention to use e-health applications.

H13. Health value moderates relationship between individual intention to adopt and use of e-health applications.

3. Research methodology

3.1 Scale measurement

The research model of this study integrates DOI theory, UTAUT model and DeLone and McLean information success model to investigate user behavior to adopt e-health applications. Therefore, research questionnaire is designed that include demographic characteristics and scale items of the constructs. Consistent with research objectives scale were adopted from prior literature due to the fact that theory is already existed against all underpinned factors. Scale instruments for social influence, effort expectancy, performance based expectancy and facilitating condition were adopted form Rahi *et al.* (2019) and Venkatesh *et al.* (2003). Therefore, scale for innovativeness and compatibility were adopted form Rahi and Abd. Ghani (2018) and Rogers (1962, 2003). Similarly, scale items for information quality, service and system quality were adopted from Rahi and Abd. Ghani (2019) and Delone and McLean (2003). Measurement items for individual intention to adopt e-health applications and user of e-health applications were adopted from Balapour *et al.* (2019), Maramba *et al.* (2019) and Rahi (2022). The research model has theorized PRV as moderating factors. Scale items for PRV were adapted from Zhang *et al.* (2019) and Deng *et al.* (2015). For scale measurement seven-point Likert scale is taken in line with prior researcher work (Rahi and Ghani, 2018; Symonds, 1924).

3.2 Sampling and data collection

The objective of this research is to disclose factors that instigate user to adopt e-health app. Therefore, fresh observations were collected using e-health app survey questionnaire.

Overall, the positivist research paradigm is taken to design the research. Concerning with population researcher has assumed smartphone user as most relevant population for this study. The reason lies in the fact that smartphone users have access of mobile apps including e-health apps. The sample size is calculated with priori power analysis. For sample size estimation effect size is taken at medium level with power of 95 and error of probability 0.05. Findings illustrate that 194 responses are sufficient for factor analysis. The priori power analysis output can be seen in Appendix 1. Concerning with data collection approach author has collected data with convenience sampling approach which is substantially used in business studies and has substantial support from prior research work (Rahi *et al.*, 2022; Ramayah *et al.*, 2016). Data were collected from Lahore city i.e. capital of province Punjab, Pakistan. During COVID-19 pandemic wave, Lahore city has remained most affected city in Province Punjab (Yasmin, 2020). In addition to that the first telemedicine center was also inaugurated in Lahore city at General Hospital Lahore (Punjab, 2020). Therefore, it is assumed that residents of Lahore city would have basic knowledge about e-health applications and will respond better to e-health application survey. Data collection process was started in September 2, 2022 and ended on third week of October 2022. Keeping in mind 194 valid sample research has distributed slightly more questionnaires among respondents. The survey questionnaire comprise an additional question whether individual are smartphone users or not. In response, respondents having smartphones were allowed to participate in research survey. Overall 280 questionnaires were distributed among smartphone users. Respondents were requested to answer statements according to their perception what they feel about e-health applications and its usage. This research is cross-sectional, and respondents have participated voluntarily. Among 280 questionnaires, 238 questionnaires were retrieved with an attractive response rate of 85%. Data were further analyzed with structural equation modeling (SEM) technique.

4. Analysis and statistical findings

The data analysis process involves confirmation of factors reliability, discriminant validity of the factors and significance of the path (Rahi, 2022). Therefore, SEM approach is incorporated. Concerning with SEM approach the variance-based approach is taken for statistical analysis. Data were estimated with Smart PLS software version 3.3 (Hair *et al.*, 2011).

4.1 The measurement model

The SEM approach is based on two stages. At first discriminant validity of the factors, convergent and discriminant validity and indicator reliability, are estimated with measurement model. Results are shown in Table 1 wherein indicator reliability has been achieved with threshold value $\geq$0.60 as recommended by Hair *et al.* (2013). Therefore, factors reliability have been confirmed with composite reliability following threshold value $\geq$0.60 in line with prior studies (Hair *et al.*, 2013; Rahi, 2017; Rahi, 2022). Similarly, convergent validity of the factors is established with average variance extracted following threshold value $\geq$0.60 as recommended by S. Rahi (2017) and Hair *et al.* (2016). Table 1 depicts satisfactory construct reliability, factors convergent validity and indicator reliability.

The convergent validity indicates that indicators are reliable and measure same construct. Therefore, discriminant validity is established with Fornell and Larcker analysis (Fornell and Larcker, 1981). This method suggests that square root of average variance extracted (AVE) must be higher than other constructs correlation. Table 2 clearly depicts

Indicators	Loading	Alpha	CR	AVE
COM1: E-health application is compatible with my lifestyle	0.811	0.853	0.910	0.772
COM2: E-health application fits well the way I like it	0.915			
COM3: E-health application is compatible to manage health tasks	0.907			
EFE1: Using e-health application would be easy for me	0.923	0.866	0.909	0.770
EFE2: I find e-health application easy to operate	0.878			
EFE3: Learning of e-health application would not be difficult	0.830			
FCO1: Enough resources are available to use e-health application	0.847	0.775	0.853	0.594
FCO2: I can get complete guidance while using e-health application	0.776			
FCO3: Necessary information is given to use e-health application	0.766			
FCO4: I get assistance if encounter difficulty in use of e-health application	0.684			
INA1: I plan to adopt e-health application in next month	0.858	0.856	0.912	0.776
INA2: I plan to adopt e-health application in next two months	0.891			
INA3: I predict I will adopt e-health application in next few months	0.894			
INF1: E-health application comprises comprehensive information	0.914	0.899	0.930	0.768
INF2: E-health application contains relevant health contents	0.855			
INF3: Information in e-health application is latest and readable	0.865			
INF4: E-health application holds attractive information about health	0.871			
INN1: If I get new technology in market I would look ways to use it	0.919	0.890	0.924	0.754
INN2: I would like to do experiments with innovative technology	0.811			
INN3: I am always first to use new technology among peers	0.954			
INN4: E-health application comprises innovative characteristics	0.777			
INU1: I would use e-health application for health related issues	0.941	0.894	0.934	0.826
INU2: I will frequently use e-health application	0.874			
INU3: I am planning to continue use of e-health application	0.910			
PER1: The use of e-health application increases my productivity	0.800	0.920	0.944	0.810
PER2: E-health application is useful to perform task	0.956			
PER3: Use of e-health application improves my job performance	0.936			
PER4: E-health application enabled me to perform tasks quickly	0.898			
PRV1: I am willing to take care of my health on serious note	0.816	0.798	0.882	0.713
PRV2: For me good health is important than anything else	0.834			
PRV3: I am ready to make any kind of sacrifice for good health	0.882			
SIN1: The use e-health applications will give me higher status	0.976	0.968	0.979	0.941
SIN2: Social environment influences me to use e-health applications	0.958			
SIN3: I recommend family and friends to use e-health applications	0.975			
SRV1: E-health application providers respond to queries at promised time and resolve issue timely	0.801	0.802	0.871	0.628
SRV2: If I need help to use e-health application service personnel quickly respond	0.776			
SRV3: Service provider pays full attention if I experience difficulty in use of e-health application	0.811			
SRV4: Service personnel have ample knowledge to answer my queries related to e-health application	0.781			
SYS1: E-health application is easy to navigate	0.867	0.881	0.927	0.808
SYS2: E-health application provides appropriate function	0.929			
SYS3: E-health application is well structured and easy to operate	0.899			

Source: Table by authors

Table 1.
Measurement model estimation

Table 2. Fornell and Larcker analysis

Factors	COM	EFE	FCO	INA	INF	INN	INU	PER	PRV	SIN	SRV	SYS
COM	0.879											
EFE	0.144	0.878										
FCO	0.089	0.060	0.770									
INA	0.706	0.164	0.150	0.881								
INF	0.577	0.103	0.096	0.658	0.877							
INN	0.322	0.042	0.107	0.457	0.444	0.868						
INU	0.412	0.148	0.039	0.405	0.357	0.315	0.909					
PER	0.353	0.058	0.108	0.435	0.375	0.259	0.213	0.900				
PRV	0.015	0.138	−0.001	−0.020	0.056	0.053	0.133	−0.103	0.844			
SIN	0.504	0.062	0.030	0.775	0.517	0.286	0.281	0.277	−0.019	0.970		
SRV	0.296	0.098	0.082	0.436	0.304	0.220	0.244	0.146	0.012	0.351	0.792	
SYS	0.409	0.106	0.002	0.458	0.294	0.264	0.214	0.182	0.016	0.323	0.223	0.899

Source: Table by authors

that AVE is greater than other constructs variance, and hence confirmed constructs are discriminant.

Factors discriminant validity is further tested with heterotrait–monotrait ratio (HTMT) analysis. According to Kline (2011), Fornell and Larcker analysis has some deficiencies and therefore discriminate validity of the factors must be tested with alternative test such as the HTMT analysis. Therefore, data are analyzed with HTMT analysis. The HTMT analysis has suggested threshold value of <0.85 or <0.90 considered satisfactory to achieve discriminant validity of the factors (Gold and Arvind Malhotra, 2001; Henseler *et al.*, 2015; Kline, 2011; Rahi, 2017). Data were estimated and results revealed that none of the HTMT value is higher than 0.90 and hence establishing discriminant validity of the factors. Findings of the HTMT analysis are depicted in Table 3.

4.2 Structural model

The structural model evaluates predictor criterion multicollinearity, path significance, effect sizes and overall variance. Nevertheless, predictor criterion multicollinearity issue could inflate or deflate data (Kock and Lynn, 2012). Therefore, predictor criterion multicollinearity

Table 3. Heterotrait–monotrait ratio (HTMT) analysis

Factors	COM	EFE	FCO	INA	INF	INN	INU	PER	PRV	SIN	SRV	SYS
COM												
EFE	0.147											
FCO	0.108	0.092										
INA	0.829	0.178	0.178									
INF	0.664	0.106	0.120	0.748								
INN	0.349	0.046	0.121	0.514	0.484							
INU	0.457	0.159	0.050	0.463	0.392	0.347						
PER	0.394	0.095	0.125	0.490	0.412	0.274	0.227					
PRV	0.037	0.155	0.080	0.045	0.067	0.061	0.158	0.122				
SIN	0.580	0.086	0.054	0.840	0.557	0.300	0.302	0.296	0.041			
SRV	0.361	0.103	0.106	0.526	0.356	0.258	0.286	0.169	0.050	0.398		
SYS	0.468	0.115	0.030	0.530	0.327	0.289	0.240	0.202	0.029	0.349	0.265	

Source: Table by authors

is tested with variance inflation factor (VIF) analysis (Kock and Lynn, 2012; Rahi *et al.*, 2022). According to Kock and Lynn (2012), predictor lateral multicollinearity can be assessed through VIF following threshold value ≤ 3.3 (Kock and Lynn, 2012; Rahi *et al.*, 2022). Findings indicate that VIF values are less than 3.3 when comparing with exogenous factors. These results have confirmed that data set is free from lateral multicollinearity issue and valid for path estimation. Results of the predictor lateral multicollinearity are shown in Table 4.

4.2.1 Assessing model goodness of fit. The research model goodness of fit is tested with model fitting parameters namely standardized root mean square residual (SRMR), normed fit index (NFI) and exact model fit, i.e. actually bootstrapped-based statistical inference (Hair *et al.*, 2016; Henseler *et al.*, 2015). SRMR shows differences between the observed correlation and model-implied correlation matrix. To ensure model fitness it is recommended that SRMS values should be less than 0.08. Therefore, results of the consistent PLS algorithm have revealed that SRMR values in saturated model and estimated model are accounted as 0.073 and 0.074 and less than threshold value. Moreover, the NFI estimates chi-square value of the model and compare against a standard benchmark. The threshold value for the NFI is suggested ≥ 0.90 (Henseler *et al.*, 2015). Nevertheless, results have revealed that NFI value was 0.913 and slightly higher than threshold value. Finally, exact model fit is measured with bootstrapping procedure. Results indicate that difference between correlation matrices was found insignificant and thus *d*ULS and *dG* < than the 95% bootstrapped quantile HI 95% of *d*ULS and HI 95% of *dG* and hence established model fitness.

4.2.2 Hypotheses testing. The hypotheses testing process includes data bootstrapping method as recommended by prior researchers (Hair *et al.*, 2011; Rahi, 2022). According to Rahi (2022), data normality issues could be reduced through bootstrapping. Therefore, data were bootstrapped with 5,000 dummy data and calculated coefficient of determination, beta value and path significance. Hypotheses testing results are shown in Table 5.

The hypotheses analysis has disclosed impact of exogenous factors in measuring adoption of e-health applications. Statistical findings had revealed significant impact of compatibility toward performance and effort expectancy and reinforced by ($\beta = 0.301$, *t*-statistics = 5.549 and *p*-value = 0.000; $\beta = 0.146$, *t*-statistics = 2.694 and *p*-value = 0.004) hence confirming *H1* and *H2*. The impact of innovativeness was found significant toward performance expectancy and reinforced by ($\beta = 0.162$, *t*-statistics = 2.631 and *p*-value =

Table 4. Assessing predictor lateral multicollinearity

Factors	Effort expectancy	Intention to adopt	Intention to use	Performance expectancy
Compatibility	1.116			1.116
Effort expectancy		1.024		
Facilitating condition		1.024		
Intention to adopt			1.000	
Information quality		1.546		
Innovativeness	1.116			1.116
Intention to use				
Performance expectancy		1.189		
Personal health value			1.000	
Social influence		1.509		
Service quality		1.189		
System quality		1.169		

Source: Table by authors

Hypotheses	Relationship	(β)	*S*-error	*t*-statistics	Significance	Decision
H1	COM → PER	0.301	0.054	5.549	0.000	Accepted
H2	COM → EFE	0.146	0.054	2.694	0.004	Accepted
H3	INN → PER	0.162	0.061	2.631	0.004	Accepted
H4	INN → EFE	0.005	0.057	0.087	0.465	Rejected
H5	PER → INA	0.144	0.030	4.773	0.000	Accepted
H6	EFE → INA	0.066	0.027	2.465	0.007	Accepted
H7	SIN → INA	0.511	0.048	1.576	0.000	Accepted
H8	FCO → INA	0.082	0.025	3.231	0.001	Accepted
H9	SRV → INA	0.112	0.027	4.118	0.000	Accepted
H10	INF → INA	0.243	0.046	5.286	0.000	Accepted
H11	SYS → INA	0.164	0.035	4.692	0.000	Accepted
H12	INA → INU	0.408	0.061	6.733	0.000	Accepted

Source: Table by authors

Table 5.
Hypothesis testing

0.004) and confirmed *H3*. Nevertheless, relationship between innovativeness and effort expectancy was found insignificant with unsatisfactory statistical values (β = 0.005, *t*-values = 0.087 and *p*-value = 0.465), and therefore *H4* was rejected.

Regarding UTAUT factors, results indicate that user performance and effort expectancy had significant impact user intention to adopt e-health applications and statistically confirmed by (β = 0.144, *t*-value = 4.773 and *p*-value = 0.000; β = 0.066, *t*-value = 2.465 and *p*-value = 0.007), and therefore *H5* and *H6* were confirmed. The social influence and facilitating factor had revealed positive impact to adopt e-health applications and confirmed *H7* and *H8* (β = 0.511, *t*-value = 1.576 and *p*-value = 0.000; β = 0.082, *t*-value = 3.231 and *p*-value = 0.001). The influence of service and information quality was found positive toward adoption of e-health applications and confirmed *H9* and *H10* (β = 0.112, *t*-value = 4.118 and *p*-value = 0.000; β = 0.243, *t*-value = 5.286 and *p*-value = 0.000). Next to this system quality had shown significant impact user behavior to adopt e-health applications and established by (β = 0.164, *t*-value = 4.692 and *p*-value = 0.000). Finally, intention to adopt had shown significant influence e-health applications and statistically reinforced by (β = 0.408, *t*-value = 6.733 and *p*-value = 0.000) and confirmed *H12*.

4.2.3 Coefficient of determination, effect size analysis and predictive relevance. The coefficient of determination R^2 is revealed collective variance of all exogenous factors toward outcome factors. Nevertheless, the effect size analysis reveal effect size $\left(f^2\right)$ of each construct independently and assists policymakers to choose right and most relevant factor. Aside of this predictive power is tested using Q^2 Stone–Geisser blind folding procedure (Geisser, 1974; Rahi *et al.*, 2021). Results of the $\left(f^2\right)$, R^2 and of Q^2 are shown in Table 6.

Results as depicted in Table 5 indicate that in determining intention to adopt e-health applications factors such as social influence have substantial effect size. Therefore, information quality has depicted medium size effect in measuring individual intention to adopt e-health applications. Concerning with DOI theory it is found that the effect of compatibility and innovativeness is small toward user performance expectancy. Therefore, in measuring effort expectancy the impact of compatibility was found small nevertheless innovativeness has shown no effect size toward user effort expectancy. Moving further e-health adoption is estimated with effort expectancy, information quality, facilitating condition, performance expectancy, social influence, service quality, system quality and revealed substantial variance (R^2 = 76.5%) in intention to adopt e-health app. Similarly, predictive relevance Q^2 was found substantial 0.575 and hence establishing that research

Factors	R^2	(f^2)	Q^2
E-health applications adoption			
Intention to adopt e-health applications	0.765		0.575
Effort expectancy		0.018	Small
Facilitating condition		0.028	Small
Social influence		0.737	Substantial
Performance expectancy		0.074	Small
Information quality		0.163	Medium
Service quality		0.045	Small
System quality		0.097	Small
Performance expectancy			
Performance expectancy		0.148	0.117
Compatibility		0.096	Small
Innovativeness		0.027	Small
Effort expectancy			
Effort expectancy	0.021		0.012
Compatibility		0.019	Small
Innovativeness		0.000	No-effect

Source: Table by authors

Table 6. Coefficient of determination, effect size and predictive power

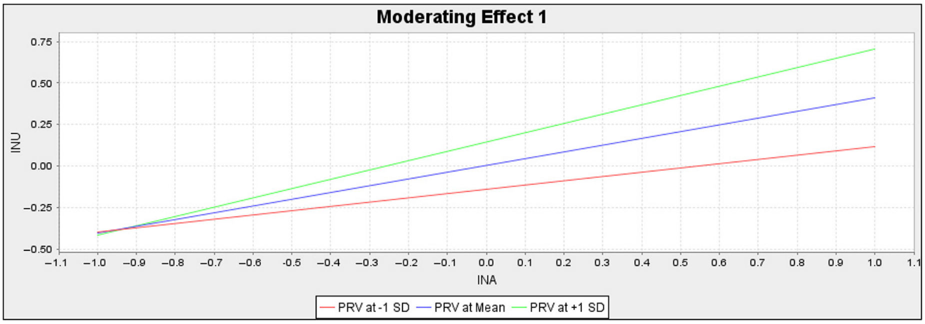
framework has satisfactory predictive relevance toward individual intention to adopt e-health applications.

4.2.4 Moderating analysis. Although this study has investigated individual behavior to adopt e-health applications with multiple factors underpinned DOI, UTAUT model DeLone and McLean framework nevertheless, the moderating effect of perceived health value is also added in current research framework. The moderating effect of PRV is theorized toward intention to adopt and use of e-health applications. To get statistical findings the product indicator approach is taken. Results revealed significant moderating role of health value between intention to adopt and use of e-health applications and statistically reinforced by ($\beta = 0.153$, t-statistics = 2.085 and p-value = 0.019), and hence *H13* is accepted. Results of the moderating analysis are shown in Appendix 2.

Aside of moderating effect power of the PRV had tested with simple slope map. According to Rahi *et al.* (2021), simple slope map assist researcher to understand whether moderating effect is positively +1 SD or negatively −1 SD moderate. Therefore, results of the simple slope analysis revealed that PRV is showing inclining trend at +1 SD gradient therefore on the flip side PRV has shown declining trend at −1 SD gradient in simple slope analysis graph. These findings have revealed that increase in individual perceived health value will strengthen the relationship between adoption of e-health app and use of e-health app. Figure 2 shows simple slope map with moderating relationship at positive and negative gradients.

5. Discussion

Over the last few decades, technology has led health organizations to introduce innovative technology in hospital for effective and efficient health services. Due to technology proliferation our societies are now becoming *superconnedcted society* wherein technology is being used for managing education, health, business operations, e-retailing and e-banking. Despite these dynamic changes fewer studies have focused on e-health adoption issue (Alam



Source: Figure by authors

Figure 2. Simple slope map source

et al., 2020). Although studies exist on telemedicine adoption among citizens during COVID-19 pandemic (Rahi, 2022), telemedicine is just a single elements of e-health information system and does not address e-health information system completely (Alam *et al.*, 2020). Therefore, this research gap is filled with integration of DOI theory, UTAUT and De and Mclean model. The integrative research model comprise factors such as effort expectancy, information quality, facilitating condition, performance expectancy, social influence, service quality, system quality and revealed substantial variance ($R^2 = 76.5\%$) in individual intention to adopt e-health applications. Statistical findings have confirmed significant impact of compatibility in measuring performance and effort expectancy of technology user and support to arguments developed by Haun *et al.* (2020) and Rahi and Abd. Ghani (2018). The role of innovativeness has been established in determining user performance and effort expectancy consistent with prior research studies (Leggott *et al.*, 2016; Rahi and Abd. Ghani, 2018).

Concerning with UTAUT theory results indicate that both performance and effort expectancy have significant impact user intention to adopt e-health applications and consistent with previous research findings (Alam *et al.*, 2020; Baudier *et al.*, 2020; Talukder *et al.*, 2020). Similarly, facilitating condition and social influence have shown positive impact individual intention to adopt e-health applications and consistent with (Alam *et al.*, 2020; Gu *et al.*, 2021; Li *et al.*, 2019). Moving further service and information quality have shown positive impact individual intention to adopt e-health applications and consistent with prior studies (Sebetci, 2018; Shim and Jo, 2020). System quality has shown significant impact individual intention to adopt e-health applications and similar to prior research findings Oderanti *et al.* (2021). Finally, impact of individual intention to adopt e-health applications was found positive and endorsing research work conducted by Tortorella *et al.* (2022). The integrated research model depicts substantial impact of social influence to adopt e-health applications. In addition to that the Stone–Geisser predictive power analysis revealed substantial power ($Q^2 = 0.575$) to predict individual intention to adoption e-health applications and hence confirmed generalizability of the research model.

5.1 Contribution to theory

In theoretical perspective, this study integrates DOI theory, the UTAUT model and DeLone and McLean model to examine individual behavior toward adoption of e-health applications. The UTAUT theory discusses about performance, individual effort expectancy, social impact and facilitating characteristics however UTAUT model does not comprise innovative factors. Consequently, this study has established that factors underpinned DOI theory namely compatibility and innovativeness are essential antecedents of UTAUT model and hence enrich information system literature. Similarly, DeLone and McLean model was integrated with UTAUT theory to uncover quality characteristics of e-health app users. The detailed literature review and statistical findings confirmed that factors such as system quality, service and information have positive impact individual intention to adopt e-health applications and hence these findings enrich information system literature. A new dimension is added in integrative research model with moderating analysis. The PRV is theorized as moderating factor between intention to adopt and use of e-health applications. Results have confirmed positive moderating impact of PRV toward individual intention to adopt and use of e-health applications. Hence, testing moderating effect of PRV toward intention to adopt and use of e-health applications contributes to both health well-being and information system literature.

5.2 Contribution to methods and practice

In methodology context, this study has numerous contributions. For instance, a latest statistical approach namely SEM is used for data analysis. Similarly, sample size is selected with priori power analysis. Aside of overall variance the effect size of the factor is computed with effect size $\left(f^2\right)$ analysis. In addition to that predictive power is tested using Q^2 Stone–Geisser blind folding procedure. Concerning with practical contribution this study has established that factors such as effort expectancy, information quality, facilitating condition, performance expectancy, social influence, service quality and system quality largely impact user intention to adopt e-health applications and therefore need managerial attention. Results have confirmed that managers should pay attention on innovativeness and compatibility which in turn enhance performance expectancy and effort expectancy of e-health applications user. In addition to that manager should pay attention in improving quality factors such as system quality, information quality and service quality which develop positive attitude and encourage technology user to adopt e-health applications. Similarly, factors underpinned UTAUT model boost e-health user confidence which in turn motivate technology user to adopt e-health applications. This study also revealed that PRV moderates the association between intention to adopt and use of e-health applications. These findings indicate policymakers should target health conscious people to increase e-health applications adoption rate and actual use of e-health applications.

6. Conclusion

Globally, e-health information system has emerged as an alternative health delivery channel. Nevertheless, adoption of e-health applications among individual is stagnant due to technology glitches. To understand e-health adoption phenomenon this study has integrated three well-known technology theories namely UTAUT model, DOI theory and DeLone and McLean model. The research design is grounded in positivism research paradigm. Empirical data is collected through survey questionnaire. Research survey was administered toward smartphone users. Overall, 238 valid responses were tested with SEM approach. Findings indicate that factors such as performance expectancy, effort expectancy, information quality, system quality, service quality, facilitating condition and social influence had shown substantial variance ($R^2 = 76.5\%$) in measuring individual intention to adopt e-health applications. Moving further effect size analysis has revealed substantial impact of social influence on individual intention to adopt e-health applications. Therefore, information quality was found the second most important factor in determining user intention to adopt e-health applications. The predictive power was tested with Geiser and

Stone's Q^2 analysis. Results revealed the current integrative model has large power to predict technology user intention to adopt and use of e-health applications. Theoretically, current study integrates three known technology models, namely UTAUT model, DOI and DeLone and McLean model to adopt e-health applications. This study confirmed moderating impact of PRV between individual intention to adopt and actual use of e-health applications and adds new dimension in e-health literature. Similarly, this research has established that compatibility and innovativeness are essential antecedents of performance expectancy and makes this research more unique and valuable. In practical context, this study suggests that managers should pay attention in improving performance expectancy, social influence, facilitating condition, system quality, service quality and information quality which develop positive behavior and encourage smartphone users to adopt e-health applications. In terms of research significance this study is first that integrates UTAUT model, DOI and DeLone and McLean model and investigates individual intention to adopt e-health applications.

6.1 Limitations and future directions

Despite several contributions to theory and practice this study has some limitations. In the first instance, the integrative research model does not claim to include all factors that influence individual behavior to adopt e-health applications. Therefore, future researchers are encouraged to extended current research model with other information system theory such as task technology fit model and expectation confirmation model. Second, this study investigates individual behavior toward traditional e-health applications that existed in app stores worldwide. Nevertheless, future research may investigate individual behavior toward adoption of specific e-health applications such as telemedicine. Another limitation of this study is to exclude user continuance intention and include user intention toward adoption of e-health applications. Future researchers may investigate that after adoption what factors influence user to continue e-health applications for long-term profitability and sustainability. This study is cross-sectional and collects data at one point in time. Nevertheless, future researchers may conduct this research in longitudinal setting to get more comprehensive picture of user behavior to adopt e-health applications. Data were collected from single city namely Lahore however future researchers are encouraged to add data from other metropolitan cities of Pakistan such as Karachi and Islamabad. Finally, future researchers are suggested to replicate current research framework in developed region which in turn enhance the generalizability of research framework.

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Appendix 1

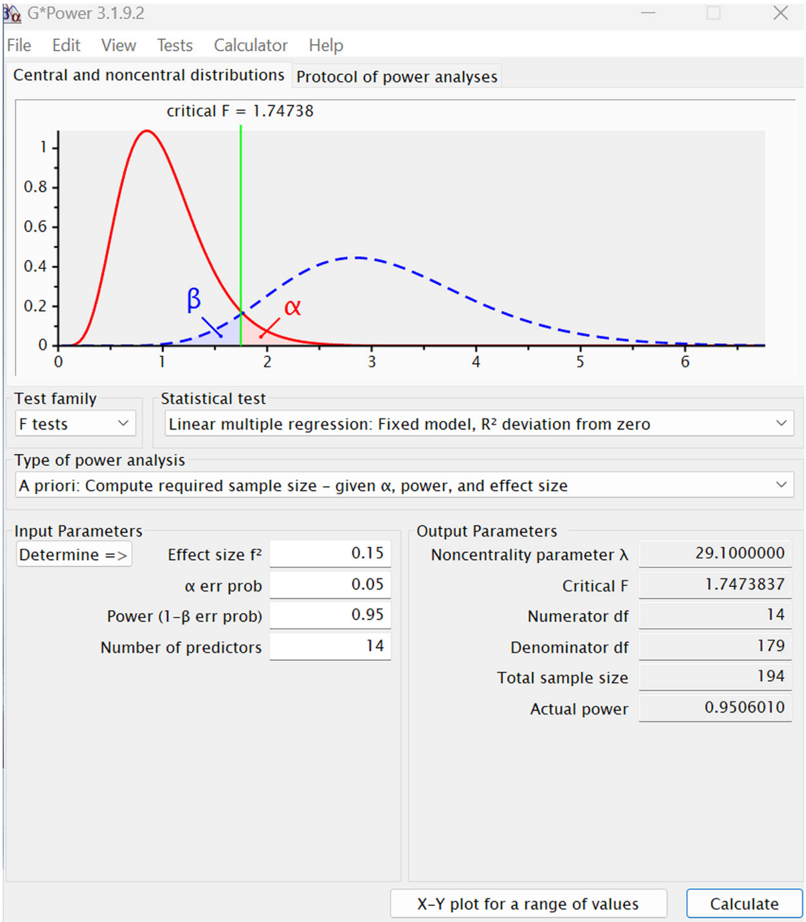
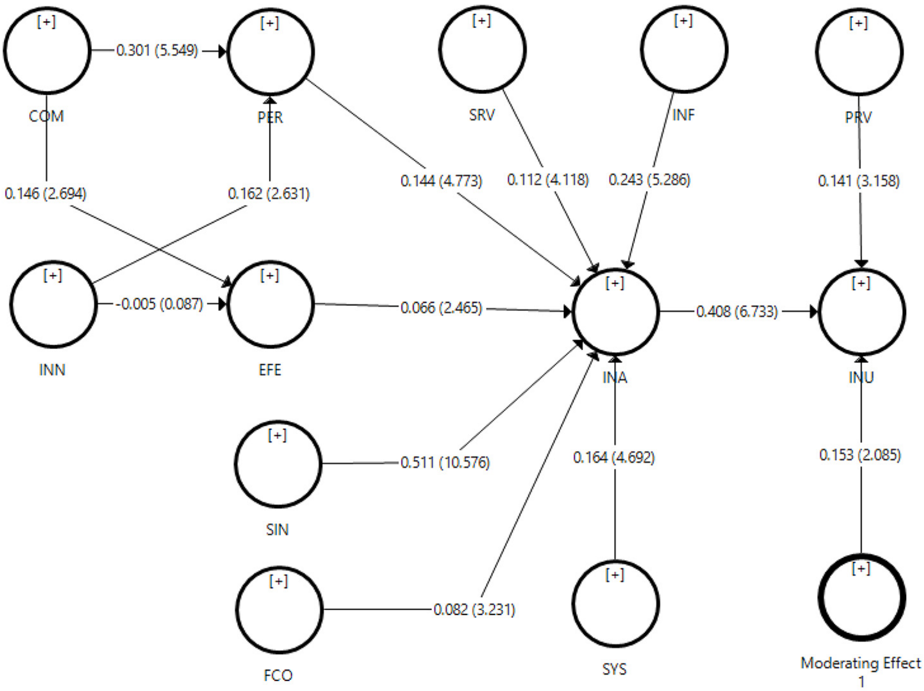


Figure A1.
Priori power analysis

Source: Figure by authors

Appendix 2



Source: Figure by authors

Figure A2. T-statistics and path coefficient

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