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Envisaging the intention and adoption of electronic health applications among middle-aged and older adults: Evidence from an emerging economy

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Abstract

Technology plays a substantial role in our daily lives, and the spread of COVID-19 paves the way for the use of healthcare technologies to manage health in the comfort of our homes. Middle-aged and older adults face health issues and require instant healthcare advice and support. Electronic healthcare (EH) applications have emerged to facilitate middle-aged and older adults receiving healthcare support instantly while remaining in their homes. The present study empirically evaluates the intention and adoption of electronic health applications with the technological attributes of perceived compatibility, cost, product value, technology accuracy, privacy issues and health motivation among middle-aged and older adults from Malaysia. Moreover, this research examines the mediating effect of the intention to adopt EH applications between technology attributes and the adoption of EH applications. This study uses a cross-sectional method and employs an online survey to assemble quantitative data from 298 middle-aged and older Malaysian adults. It utilizes partial least squares structural equation modelling for data analysis. The data analysis reveals that perceived compatibility, cost, privacy, product value and health motivation significantly influenced the intention to use EH apps. Furthermore, the analysis shows that the intention to adopt EH apps significantly mediates the relationship between the perception of cost, personal privacy, product value, health motivation and adoption of EH apps. However, the intention to use EH apps insignificantly instigates their adoption. Finally, the study presents its implications, limitations and future research directions.

Keywords

Electronic health applications, intention, adoption, values, compatibility, privacy

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Introduction

With the progress in digital technology and the occurrence of the COVID-19 pandemic, new healthcare inventions, such as wearable medical devices, have caused a surge of eagerness to use healthcare technology.[1] Users need simple technology that meets their demands to depict their health condition promptly and precisely.[2] However, the ageing population has recently increased; approximately 35% of the world's inhabitants are in their early 40s.[3] The global elderly population may reach 2 billion by 2050.[4] These users seek individualized healthcare services, including self-health management or instant health assessment applications.[5] The increased demand for healthcare technology initiates the permeation of various smart healthcare wearable gadgets available today that screen and monitor fitness.[6]

The market demand for electronic health applications is regularly rising and may reach USD 700 billion by late 2030 with annual growth of 16%.[4] Technology firms are inclined towards the rising market for electronic health

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opportunities. New applications and aspects are attributed to electronic health applications that enable users to undergo their health checks at their convenience.[7] Electronic health applications empower users to evaluate their daily health conditions such as daily physical undertaking, food consumption quality, diet nutrition rate, sleep value, pulse frequency and overall health conditions, empowering users to live independently.[8]

Different electronic health applications are available in the market, empowering users to screen and thrive in their personal health with smartwatches, smart bands, mobile phone–built gadgets and web-based health applications.[2] Malaysian consumers are infiltrated by brands such as FitBit, Apple Watch, Samsung Galaxy Watch and Honor Smart Watch, as well as online health applications.[9] These technologies allow users to efficiently screen and maintain health situations in the comfort of their homes.[10] Electronic health applications empower users to reduce health hazards and scan their body temperature, heartbeat amount, daily movement and different health situations.[7] Furthermore, healthcare centers highly suggest adopting e-health services, as e-health applications facilitate recording patients' health conditions and offer crucial insights to doctors to treat patients.[4]

Malaysia is an emerging economy working to provide state-of-the-art public healthcare services by improving public health. Internet and mobile use penetration is the highest in Malaysia among Southeast Asian countries. The Malaysian government is looking to use the Internet and mobile technology to attain a healthy nation, empowered through digitalization, by 2030, as proposed in the Twelfth Nation Plan.[11] The delivery of healthcare services through technology requires digital infrastructure to offer healthcare services at an affordable cost, with quality and convenience. Another objective associated with the penetration of digital healthcare services is to reduce healthcare delivery costs, as Malaysia is experiencing a 13.5 inflation-index in healthcare costs.[3]

Furthermore, healthcare service professionals are fewer in Malaysia compared with world standards, with only 1.5 competent doctors and 3.5 trained nurses per 1000 people.[12] The growing elderly population needs efficient health services. Malaysia has reached the status of an aged nation, as 7% of the population is between 60 and 65 years old.[3] By 2050, 23% of Malaysia's population will be aged between 60 and 65 years.[3] Furthermore, the median age of Malaysians reached 31 years, and the median age will reach 41 years by 2050.[13] Now, 26% of the Malaysian population is aged between 40 and 60 years and may be categorized as middle-aged as Malaysia plan to term the youth between 16 and 39 years.[3] With the ageing population, health issues became obvious, and increasing personal health expenses caused financial and social hardships for the ageing population.[4] Therefore, digital healthcare service is an excellent option for expanding healthcare services through prompt delivery offered at users' convenience and can thereby ensure a healthy nation.

However, the question remains: 'How do electronic health technology-based application attributes and personal health motivation persuade the intention and adoption of electronic health applications (EH Apps) among middle-aged and older adults?' In addressing this query, the present study explores the intention to adopt electronic health applications with technological features (compatibility, cost, personal privacy, product value, technology accuracy and health motivation). The later adoption of EH Apps was promoted by health motivation (HMT) and intention to adopt EH Apps among Malaysian adults.

Literature review

Theoretical foundation

The adoption of technology remains a stimulating topic among scholars. Major theories addressing this include the technology adoption model, diffusion of innovation (DOI) and unified theory of acceptance and use of technology.[8,14] Technology attributes remain imperative inducing factors encouraging the adoption of technologies.[15] Technology compatibility, perception of cost, value and accuracy remain significant attributes instigating most technologies' formation, intention and use.[16] However, such technologies and gadgets that require user information, such as mobile phone services, healthcare gadgets and social media platforms, are plagued by privacy issues. Therefore, the issue of user privacy is imperative and can either instigate user adoption or curtail it. However, the popular perception regarding the use of technology is one of benefit, and therefore, users tend to rely on them as well. Hence, exploring individual HMTs' effect on triggering healthcare technology adoption is worthwhile.

Hypotheses development

Perceived compatibility. Perceived compatibility (PCM) refers to how much new technology integrates with the prevailing use of technologies and the daily lifestyles of users.[17] For healthcare technology, compatibility is pronounced as the capability of the technology to offer users health-associated data that can promote users' well-being and continuous intention to use healthcare technologies.[18] Compatibility is also designated as aligning innovation with latent consumers' prevailing product values, contemporary needs and lifestyles.[19] Technology compatibility facilitates the use of healthcare technology among users.[6] It is regarded as an active component of implementing cutting-edge technologies and significantly affects users' behavioural intentions.[16] Thus, we propose the following hypothesis:

H1a: *PCM has a positive influence on the intention to use EH Apps.*

Perceived cost. Perceived cost (PCO) is a prime characteristic that regulates buyers' reception of technology.[20] The level at which a person assumes that using wearable medical equipment costs money is characterized as PCO.[21] The costlier wearable health gadgets are, the less likely people are to use them. Users normally demand a superior-quality product at a rational, lower cost.[22] Reasonable price promotes a positive attitude towards using innovative technology.[20] The reasonable price of technology forms the desire to use healthcare technologies.[21] Therefore, we propose the following hypothesis:

H1b: *PCO has a positive influence on intention to use EH Apps*.

Perceived personal privacy. Perceived personal privacy (PPP) remains a vital aspect of healthcare technology, as personal information and healthcare statistics are available online and can be retrieved by other users. Personal privacy is defined as the loss of secrecy and protection from misuse of personal information.[23] Healthcare technology users always show concern for privacy and personal security, negatively influencing healthcare technology adoption.[24] The awareness of privacy issues with healthcare inventions influences the intention to adopt healthcare technology.[25] In view of the studies mentioned above, the following hypothesis is proposed:

H1c: *PPP has a negative influence on to the intention to adopt EH Apps*.

Perceived product value. Technology promises to bring value to consumers. Users estimate the benefits of using technology and compare them with associated costs. The cost–benefit ratio builds the notion of product value.[26] Product value awareness describes the user's evaluation that depicts the product's utility and harnesses the user's intention to use the technological invention.[22] The use of technological healthcare services is based on the general perception of the utility and value provided by healthcare products. Prospective users pay attention to healthcare product value, instigating behavioural intent to use healthcare services.[26] Thus, we propose the following hypothesis:

H1d: *PPV has a positive influence on the intention to adopt EH Apps*.

Perceived technology accuracy. Technology requires accuracy, and the perception of the technology's accuracy nurtures the motivation to use the technology.[27] Perceived technology accuracy depicts that consistency and correctness promote the use of healthcare technology.[28] Insight into healthcare technology offers users a value perception that instigates the intention to use healthcare inventions.[20] Healthcare devices must accurately provide precise health conditions and the best available healthcare. Thus, we hypothesize the following:

H1e: *PTA has a positive influence on the intention to adopt the EH Apps*.

Health motivation. Health motivation depicts the innate desire to engage in health-related preventive behaviours.[29] Highly health-motivated individuals are involved in precautionary activities and actively engage in healthcare technologies.[9] Health motivation instigates the use of wearable healthcare devices and allied technologies.[19] Individual health stimuli trigger the purchase behaviour concerning healthcare technology. Higher HMT harnesses health concerns and prompts the intention to use healthcare gadgets and appropriate healthcare technologies.[28] Thus, we propose the following hypotheses:

H1f: *HMT has a positive influence on the intention to adopt the EH Apps*.

Adoption of EH apps

Health motivation. Health motivation enables healthcare technology adoption as potential users have adequate data and have formed the opinion to use healthcare technologies. Individual HMT triggers technology use and reduces the perceived risk of healthcare technology.[28,30] Accepting healthcare technology is an individual choice, and personal healthcare concentration promotes embracing healthcare technology. Therefore, we propose the following hypotheses:

H2: *HMT has a positive influence on the adoption of EH Apps*.

Behavioural intention is the desire to engage in specific behaviours or perform a particular behaviour.[8,14] The intention is a suitable indicator of actual behaviour.[28] Thus, the following hypothesis is proposed:

H3: *Intention to adopt EH has a positive influence on the adoption of EH Apps*.

Mediational effect of intention to adopt EH apps. Technology compatibility is a dynamic aspect that drives the acceptance of healthcare technology, thereby depicting the ease of use.[6] The perception of compatibility facilitates the development of intention and harnessing healthcare technology adoption.[19] We expect that the intention to use healthcare technology will mediate between healthcare technology compatibility and the approval of healthcare innovations. Technology cost is a vibrant attribute that promotes intention and technology adoption.[9] An individual compares the technology cost and prices with its benefits, and technology prices must be more reasonable than their

counterparts available in the market.[15] The perception of technology price facilitates acceptance by harnessing the intention to adopt healthcare technologies.[20]

The acuity of personal security and privacy in healthcare technology is essential for users. The perception of healthcare technology with acceptable privacy harnesses its intention and espousal of healthcare technology.[25] Privacy concerns trigger the intention to harness the adoption of healthcare technologies. Product value allows the individual to consider whether technology is valuable for prospective users and can be regarded as offering affordable utility.[26] A higher perception of technology value is associated with the intention to use the technology and the adoption of authentic technology.[10,22] The perception of technology accuracy brings awareness of the worthiness and accurate reporting of health conditions, creating the intention to adopt healthcare technologies.[20] The positive intention formed by technology accuracy triggers the adoption of healthcare technology.[30] Therefore, the intention to adopt healthcare technology may mediate between awareness of technology accuracy and the adoption of healthcare technology. The awareness that health is vital for a healthy life and the emphasis on leading a healthy life prompts the intention to use healthcare devices that instantly offer health measurements.[9] Health motivation activates the use of healthcare technologies, which, in turn, activates healthcare technology adoption.[19] Consequently, we propose the following hypotheses:

$H_{M1\text{-}6}$: *The association between the PCM, PCO, PPP, PPV, PTA and HMT on adopting EH Apps is mediated by the intention to adopt the EH Apps.*

Methodology

Population and sample

The sample size for the study was premeditated by consuming G-Power 3.1 with a power of 0.95 and an effect size of 0.15. The mandatory sample size for the current study was 153, with seven interpreters.[31] Partial least squares structural equation modelling (PLS-SEM) requires a 200-sample threshold.[32] This study relies on convenience sampling, a non-probability method for gathering data. The online survey gathered responses from middle-aged and older adults (age 40 and above) in Malaysia who were aware of healthcare technologies to screen their health. A pre-qualification question was asked in the survey: the 'respondent is aware of the Electronic health application'. If a respondent was unaware of the EH Apps, s/he was not permitted to participate in the main survey. Data analysis was performed with 298 effective responses collected between 12th and 28th November 2021. The ethics committee (Ethical Review of Biomedical Research Involving Human Beings, China) ruled that no formal ethics approval was required, and business and management studies only require clear and explicit informed consent prior to data collection. This study has been performed following the Declaration of Helsinki. Written informed consent for participation was obtained from respondents who participated in the survey.

Measurement scales

This study adopted recognized and well-established research instruments to collect data. Perceived compatibility was estimated using four question items taken from Tan and Ooi.[33] An example of a question statement was, 'I contemplate using electronic health apps ensembles my way of dealing with my health at home'. Three items were used to measure the perceived concern for electronic health apps taken from Kim et al.[34] The model question item was, 'I am satisfied with the electronic health app charges'. Perceived personal privacy was appraised using four statements from Gao et al.[35] An example question declaration was, 'It would be risky to release my health information to an electronic health app provider'. The perceived product value (PPV) of electronic health apps was estimated using four question items taken from Kim et al.[34] An example question item was 'I think electronic health apps are worthwhile'. The current study estimated the perception of technology accuracy using four question items taken from Alam et al.[9] An example of a question item was, 'I feel confident that using electronic health apps offers error-free results'. Health motivation was evaluated using the four items derived from Li et al.[36] The question was, 'I am familiar with how to avoid health problems'. The intention to adopt the electronic health app was gauged using four items engaged from Alam et al.[14] and Gao et al.[35] An example of question declaration was, 'I would be willing to develop the habit of using electronic health apps'. The use of electronic health apps was gauged using a single-question item. All questionnaire statements for exogenous variables were appraised using a five-point Likert scale, whereas endogenous variables were estimated using a seven-point Likert gauge. In the study design phase, employing separate Likert scales for input and outcome constructs resolves the problem of common method variance.[37] See Figure 1 for study model.

Common method variance (CMV) assessment

The consequences of CMV as an investigative method were estimated using Harman's one-factor assessment. The single factor was 33.65%, which is less than the threshold limit of 50% in Harman's one-factor test, demonstrating no CMV issue in the current data.[37] Furthermore, the study evaluated the CMV by testing the complete collinearity of all constructs.[38] The variance inflation factor (VIF) for HMT (1.618), PCM (1.710), PCN (1.851), PTA (1.670), PPC (1.788), PPP (1.791), intention to adopt EH

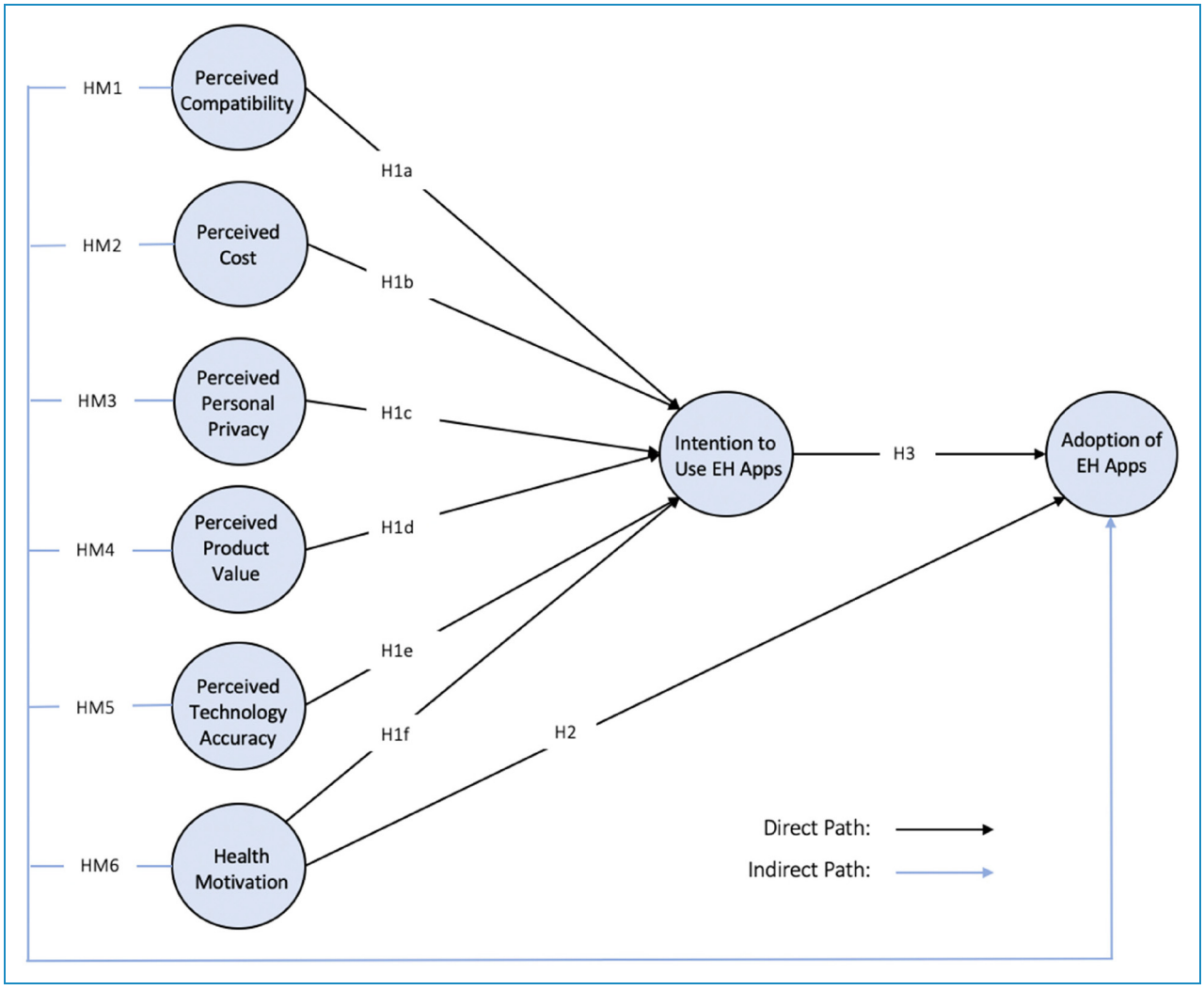

Figure 1. Research framework.

Apps (1.950) and adoption of EH Apps (1.845), all VIF scores were below 3.3, demonstrating no issue bias in the uni-sourced data.[37]

Testing multivariate normality

The multivariate normality for the dataset was measured using the online Web Power tool (https://webpower.psychstat.org/wiki/tools/index). The premeditated Mardia's multivariate skewness, kurtosis coefficient and *p*-values displayed that the study data had an issue of non-normality, as the *p*-values were less than 0.05.[39]

Study data analysis

Applying SmartPLS 3.2, PLS-SEM was used to assess the suggested model and analyze the hypotheses. The PLS-SEM procedure for hypothesis testing has been validated in numerous research studies and is recurrently utilized.[32] This technique's plasticity in data distribution makes it suitable for small sample sizes.[38] Verifying the constructs' reliability and convergent and discriminant validity is the first step in PLS-SEM.[40] Cronbach's alpha (CA) measures reliability, and Dillon-Goldstein's rho, composite reliability (CR) and average variance extracted (AVE) gauged internal consistency reliability.[32] Furthermore, discriminant validities were estimated using the Fornell–Larcker criterion, the heterotrait-monotrait ratio (HTMT) and loadings and cross-loading. The hypothesis was tested by implementing the bootstrapping process with 5000 samples and using the coefficients (Beta), confidence interval, t-value and *p*-value.[40] Model quality estimation implemented with the r^2, Q^2 and effect size (f^2), r^2 offers the level of variance explanation in the model, where Q^2 depicts the predictive relevance of the model part when multiple outcomes are part of a model, and f^2 shows the effect size of each input variable in the outcome variable.[32] The mediation analysis was implemented using the 5000

resampling with bias-corrected bootstrapping. The confidence interval for specific indirect paths was evaluated with (confidence low and confidence high) and '0' did not arrive between the low and high confidence interval, suggesting the acceptance of mediation analysis.[32]

Results

Respondents demographic

As shown in Table 1, most respondents (51.4%) were female, while 48.6% were male. Respondents' ages ranged as follows: 40–45 years (16.1%), 46–50 years (18.1%), 51–50 years (22.8%), 55–60 years (21.8%) and 60 years and above (21.2%). Most respondents had a master's degree (22.8%), followed by a doctorate level (21.8%), a bachelor's degree (20.5%), a diploma (18.1%) and 16.8% held only a secondary school certificate. The respondents' average monthly income ranged as follows: 16.2% had an average monthly income below RM 2,500, 14.8% between RM 2501–5,000, 21.1% between RM 5001–7,500, 18.4% between RM 7501–10,000, 14.4% between RM 10,001–12,500 and 15.1% had an average monthly income above RM 12,500. The respondents' province-wise segregation was as follows: Kuala Lumpur (16.1%); Pahang (14.4%); Penang (12.7%); Sarawak (11.7%); Terengganu (11.1%); Johor Bahru (12.2%); Kelantan (12.4%) and Kedah (9.4%).

Partial least squares structural equation modelling analysis

Reliability and validity. The measurement model facilitated the assessment of the construct's reliability and validity. The reliabilities were estimated (as presented in Table 2) using CA, DG rho and CR; the reliabilities for each construct must surpass the 0.65 benchmarks.[32] All CA values were above 0.65, and the smallest value attained by INT was 0.651.[32] The DG rho values for all constructs were above 0.65, except INT, which was 0.665. Correspondingly, the CR values for all constructs were above 0.65, thus achieving the construct's level of reliability and being viewed as acceptable. The AVE for every construct surpassed 0.50, thereby confirming convergent validity.[32] Furthermore, the VIF must be less than 3.3.[40] No multicollinearity exists because the VIF values of all variables were less than 3.3.[38]

The existing work's discriminant validity was assessed using the Fornell–Larcker criterion, HTMT ratio, and with loading and cross-loading. The AVE square root of each construct must be higher than the maximum squared correlation of the variables. The Fornell–Larcker criterion confirms the discriminant validity of the current model. Second, the HTMT ratio must be below 0.90, and the result suggests that all HTMT ratios were smaller than 0.90, indicating discriminant validity for all research constructs.[40] Lastly, the loading and cross-loading values of the constructs satisfying the construct items significantly loaded on their specific constructs, suggesting discriminant validity for the current model. The outcomes are presented in Supplementary Material S1. Discriminant Validity.

Hypothesis testing. The adjusted r^2 score for intention to use the EH Apps from the six input constructs (i.e., PCM, OCN, PTA, PPV, PPP and HMT) indicated 30.1% of the variation in the intention to adopt EH Apps. The predictive relevance of the Q^2 score for this model portion was 0.140% and displayed medium predictive relevance.[41] The path between PCM and INT reveals that PCM is significantly positively related to INT, thus supporting H1a. The f^2 value of 0.006 indicated a small effect of the PCM on the INT. The path value between PCN and INT exhibits that PCN had a significant positive consequence on INT, suggesting acceptance of H1b. An f^2 value of 0.065 indicated a medium effect of PCN on INT.[32] The path value between PPP and INT shows that PPP had a negative and significant effect on INT, suggesting acceptance of H1c. An f^2 value of 0.016 indicates a small effect of PPP on INT.[32] The path value between PPV and INT shows that PPV significantly positively affects INT, thus supporting H1d. An f^2 value of 0.099 indicates a medium effect of PPV on INT.[32] The path coefficients for PTA on INT have a negative but significant effect. An f^2 value of 0.016 indicates a medium effect of PTA on INT.[32] This result suggests the rejection of H1e. The path coefficients of HMT on INT have a significant positive effect. An f^2 value of 0.040 indicates a medium effect of HMT on INT.[32] This result supports H1f. Table 3 and Figure 2 present the findings of this study.

The adjusted r^2 value for ADT with the two participatory constructs (i.e., HMT and INT) illustrates 3.4% of the variation in ADT explained by HMT and INT. The predictive relevance of the Q^2 value of the model was 0.029, showing a small predictive relevance.[41] The effect of HMT was positive and supported H2. An f^2 value of 0.029 indicates a medium effect. The effect of INT had a negative and significant influence on ADT, thus supporting H3. An f^2 value of 0.020 indicates a small and medium effect.[32] The result is presented in Table 3, see the Figure 2 for model assessment.

Mediational analysis. Mediation analysis revealed that INT insignificantly mediates the connection between PCM and ADT, consequently offering no sustenance to admit HM1. This result suggests that INT significantly mediates the association between PCN and ADT in accepting HM2. Subsequently, the path between PPP and ADT ($\beta = 0.016$, $p = 0.033$) indicated that INT significantly mediated the path, suggesting acceptance of HM3. The outcome revealed that INT significantly mediated the path between PPV and ADT, providing a backing to admit HM4. Consequently, INT

Table 1. Demographic features.

	N	%		*N*	%
Gender			*Education*		
Male	15	48.6	Secondary school certificate	50	16.8
Female	153	51.4	Diploma	54	18.1
Total	298	100	Bachelor's degree or equivalent	61	20.5
			Master's degree	68	22.8
Age			Doctoral Degree	65	21.8
40–45 years	48	16.1	Total	298	100
46–50 years	54	18.1			
51–55 years	68	22.8	*Average Monthly Income*		
56–60 years	65	21.8	Below RM 2500	48	16.2
Above 60 years	63	21.2	RM 2501–RM 5000	44	14.8
Total	*298*	*100*	RM 5001–RM 7500	63	21.1
			RM 7501–RM 10,000	55	18.4
Living Province			RM 10,001–RM 12,500	43	14.4
Kuala Lumpur	48	16.1	More than RM 12,500	45	15.1
Pahang	43	14.4	Total	298	100
Penang	38	12.7			
Sarawak	35	11.7	*Used healthcare application*		
Terengganu	33	11.1	Never used	42	14.1
Johor Bahru	36	12.2	More than one month	46	15.4
Kelantan	37	12.4	More than half a year	58	19.5
Kedah	28	9.4	More than one year	50	16.7
Total	298	100	More than three years	47	15.8
			More than five years	55	18.5
			Total	298	100

insignificantly mediates the connection between PTA and ADT, offering no indication to admit HM5. Later, the decision showed that INT significantly mediated the path between HMT and ADT, providing help to acknowledge HM6. The results are presented in Table 4.

Discussion and conclusion

The present work aimed to identify the factors that can facilitate the development of intention and adoption of EH Apps among Malaysian adults. For the current study,

Table 2. Reliability and validity.

Variables	No. of items	CA	*rho_A*	CR	AVE	VIF
PCM	3	0.727	0.788	0.832	0.625	1.848
PCN	3	0.759	0.776	0.860	0.672	1.358
PPP	3	0.853	0.850	0.905	0.765	1.818
PPV	4	0.755	0.794	0.843	0.575	1.706
PTA	4	0.800	0.859	0.809	0.526	1.691
HMT	3	0.664	0.665	0.813	0.593	1.710
INT	3	0.651	0.672	0.786	0.551	1.509
ADT	1	1.000	1.000	1.000	1.000	-

PCM: perceived compatibility; PCN: perceived cost; PPP: perceived personal privacy; PPV: perceived product value; PTA: perceived technology accuracy; HMT: health motivation; INT: intention to use EH Apps; ADT: adoption of EH Apps; CA: Cronbach's alpha; *rho_A*: *rho*; CR: composite reliability; AVE: average variance extracted; VIF: variance inflation factors.

Table 3. Hypotheses testing.

No.	Path	Coefficients	CI – Min	CI – Max	*T*	*p*	r^2	Q^2	f^2	Decision
Factors for intention to adopt EH Apps							0.310	0.140		
H1a	PCM → INT	0.074	0.004	0.149	1.687	0.046			0.006	Supported
H1b	PCN → INT	0.290	0.161	0.382	4.334	0.000			0.065	Supported
H1c	PPP → INT	−0.111	−0.175	−0.058	2.528	0.006			0.016	Rejected
H1d	PPV → INT	0.193	0.194	0.392	4.963	0.000			0.099	Supported
H1e	PTA → INT	−0.061	−0.123	0.060	0.992	0.152			0.003	Rejected
H1f	HMT → INT	0.170	0.106	0.235	4.256	0.000			0.040	Supported
Adoption of EH Apps										
H2	HMT → ADT	0.171	0.098	0.247	3.794	0.000	0.038	0.029	0.029	Supported
H3	INT → ADT	−0.141	−0.212	−0.066	3.211	0.001			0.020	Rejected

PCM: perceived compatibility; PCN: perceived cost; PPP: perceived personal privacy; PPV: perceived product value; PTA: perceived technology accuracy; HMT: health motivation; INT: intention to use EH Apps; ADT: adoption of EH Apps.

we utilized the factors of technology compatibility, cost, personal privacy, technology accuracy, technology value and HMT, which may impact the intention to use EH Apps. In addition, HMT and intention to use EH Apps instigate the adoption of EH Apps.

Our findings suggest that the PCM of EH Apps is significantly related to the intention to adopt EH Apps. Our work outcome coincides with the effect that Ahmad et al.[18] postulated that technology compatibilities offer greater acceptance of health-associated technologies. A higher perception of technology compatibility demands less time and personal resources to build a positive intention to practice healthcare technology. Perception of technology compatibility is critical in building the intention to use technology that can offer advantages over currently available technologies.[19] However, the current study findings

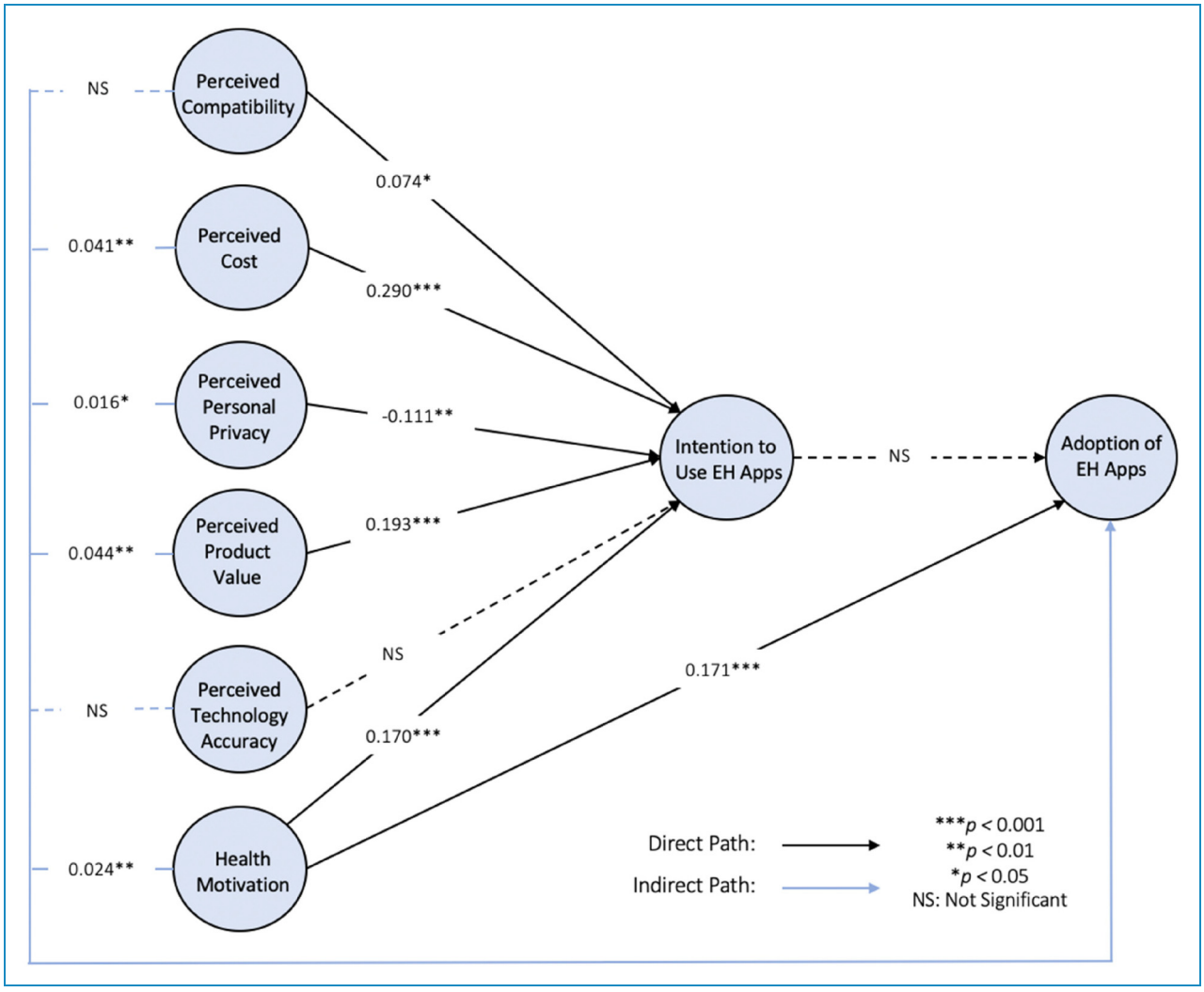

Figure 2. Study assessment model.

Table 4. Mediational analysis.

Hyp.	Path	Coefficients	CI – Min	CI – Max	*t*	*p*	Decision
HM1	PCM → INT → ADT	−0.010	−0.023	0.000	1.473	0.070	No mediation
HM2	PCN → INT → ADT	0.041	0.014	0.067	2.541	0.006	Mediation
HM3	PPP → INT → ADT	0.016	0.005	0.031	1.842	0.033	Mediation
HM4	PPV → INT → ADT	0.044	0.011	0.071	2.460	0.007	Mediation
HM5	PTA → INT → ADT	0.009	−0.007	0.020	1.023	0.153	No mediation
HM6	HMT → INT → ADT	0.024	0.012	0.048	2.571	0.005	Mediation

PCM: perceived compatibility; PCN: perceived cost; PPP: perceived personal privacy; PPV: perceived product value; PTA: perceived technology accuracy; HMT: health motivation; INT: intention to use EH Apps; ADT: adoption of EH Apps.

suggest an insignificant mediation of intention among the EH App compatibility and adoption. It reflects that the compatibility of EH technology did not successfully predict the adoption of EH Apps. The subsequent hypothesis estimates the association between PCO and intention to use EH Apps. The study finding matches the outcome of Bandara and

Amarasena,[20] who found that reasonable technology cost substantially builds a positive intention to adopt the technology. Rational pricing of technology expected to harness the intention to adopt healthcare technologies.[5]

Additionally, the intention to adopt EH Apps significantly mediates the association between the technology cost and the adoption of EH Apps. Our result confirms that the EH Apps cost is a valid interpreter that can be used to predict the adoption of EH Apps through the intention. High-quality healthcare technologies must be reasonably priced to benefit the consumer and reduce the financial load on healthcare arrangements.

Next, the current study aims to evaluate the association between PPP and the intention to adopt EH Apps. The outcome depicted an adverse association between PPP and intention to adopt EH Apps. Our findings take their sustenance from Dhagarra et al.,[23] which posit that a low perception of personal privacy expected to reduces the intention to use the technology. The loss of privacy and the perception that the technology service provider can mishandle users' data lead to a lower intention to use healthcare technology.[25] Nevertheless, the intention to adopt EH Apps significantly mediates the relationship between the PPP and the adoption of EH Apps. Personal privacy and the notion that users' data are secure can harness their intention to adopt healthcare technology. Subsequently, a significant positive connection occurs between PPV and the intention to adopt EH Apps. The conclusion of our work accords with the outcome recognized by Xinyan et al.,[22] namely that the perception of value facilitates the intention to adopt healthcare technology. The perception of value is associated with considering that technology offers users utility and value for money.[26] The mediational analysis settles that the intention to adopt EH Apps mediates the association between the perception of value and the adoption of EH Apps. As rational consumers, EH Apps users estimate the expected value drive from using EH Apps and only adopt the EH Apps when the expected value from using EH Apps exceeds the expected cost associated with the purchase and use of EH Apps.

The following premise evaluates the relationship between PTA and intention to adopt EH Apps. The results of our study suggest a negative but insignificant connection between PTA and intention to adopt EH Apps. This research finding is much different than the prevailing literature. It suggests that low PTA can lead to the low intention and non-adoption of EH Apps among the study sample. As we know, health management is a sensitive issue, and healthcare technology must offer accurate health data depicting a user's health conditions for personal use or by medical professionals. It is imperative to suggest that healthcare technology that offers consistent, precise and exact human vitals builds the intention to use healthcare technologies among users. The insignificant mediation between the EH Apps technology accuracy and adoption through the intention also suggests improving the EH Apps accuracy and consistently building the current users' confidence in using EH Apps. The following proposition of the current work assesses the relationship between individual HMT and the intention to adopt EH Apps. The results described a constructive and substantial connection between HMT and intention to adopt EH Apps. Our study finding is supported by the work of Asadi et al.,[19] who found that individuals with higher health-associated motivation are more likely to use healthcare technology. Lee and Lee[9] established that HMT harnesses the precautionary behaviour that leads to the intention to adopt healthcare technology. The mediational analysis also recommends a mediation of intention between the HMT and the adoption of EH Apps. Health motivation is a major driving force linking healthcare gadgets and related technology usage among middle-aged individuals and elders.[29]

The succeeding premise estimates the association between HMT and adopting EH Apps. The investigation established a noteworthy and positive link between HMT and adopting EH Apps. Our study findings coincide with the results of Cheung et al.,[28] as an individual with a higher level of HMT is more inclined towards using health technology. Health motivation builds the interest and inclination to try and experiment with novel health-related technologies, empowering users to manage their health.[16,19] Finally, the intention to adopt EH Apps is significantly but negatively related to the adoption of EH Apps. Our current results diverge from the work of Lee and Lee[9] and Alam et al.,[14] which signifies that the current study respondents are concerned about adopting EH Apps. The low adoption of EH Apps suggests that middle-aged people and elders are not currently ready to adopt EH Apps.

Theoretical inferences

The current work examines the attributes of PCM, cost, personal privacy, product value, technology accuracy and HMT that can promote the construction of intention and resultant adoption of EH Apps. The study results contribute to the DOI that the EH app attributes help form a positive intention towards adopting healthcare technology. Furthermore, HMT significantly initiates the intention to adopt healthcare technologies. The current work contributes to the technology adoption literature and helps devise relevant policy guidelines for harnessing the mass adoption of healthcare technologies.

Moreover, recent research only discusses technology attributes; however, HMT also plays a significant role in adopting healthcare technologies that may be available electronically or in terms of healthcare devices.[42] However, middle-aged people and elders in emerging economies are showing low adoption of EH Apps. It suggests that middle-aged people and elders must be encouraged to

start using EH apps to promote personal privacy, technology accuracy and HMT.

Practical and managerial implications

This study offers managerial implications for electronic health application marketers, developers and managers. Perceived personal privacy and technology accuracy are essential aspects of harnessing the intention to use healthcare technology. In the current work, these factors were negative and insignificantly predicted the intention to adopt EH Apps. Hence, developers and management personnel of EH Apps must consider expanding and improving privacy and accuracy. Furthermore, the perception of compatibility is low among the middle-aged and elders coming from emerging economies. Thus, it may negatively influence the construction of an intention and adoption of EH Apps. The developers of EH Apps need to considerably enhance the ease of use of EH Apps and make these EH Apps easier to use, which can empower users to obtain maximum advantages from using EH Apps.[1] Lastly, marketers and management personnel of EH Apps need to engage users and design accessible and easy-to-follow instructions to use EH Apps that can improve compatibility and perception of accuracy. This can be done by making instructional videos to help existing and prospective EH app users.

Study limitations

The present study is associated with three pertinent limitations. First, data were collected from Malaysia and thus have limited generalization value. Therefore, replicating the current study with other geographical locations is suggested to generalize the current study model better. Second, a limited number of factors are utilized to evaluate the formation of an intention to adopt EH Apps. More relevant and consistent factors may be added to fully discover the creation of the intention and adoption of EH Apps. Lastly, the current work is based on the deductive approach, where data were collected through a questionnaire in a cross-sectional manner, offering generalization but a low level of exploration. Future studies must assume a longitudinal and explorative research strategy to focus on a more appropriate exposure for evaluating the construction of the intention and adoption of EH Apps.

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