

Integrating UTAUT2 and VAM to explain intention to use AI fitness coaching: The roles of perceived value and privacy, and the moderating role of EWOM

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Abstract

In the context of rapid digital transformation in Vietnam, AI fitness coaching is increasingly gaining attention as a technology-driven solution for personalized fitness management and health-related behavior support. However, empirical evidence on the factors shaping users' intention to use this service remains limited. To address this gap, this study integrates the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Value-based Adoption Model (VAM) to examine the determinants of intention to use AI fitness coaching. It also investigates the moderating role of electronic word-of-mouth (EWOM) in the relationship between perceived value and intention to use. Data were collected through direct, on-site administration of a structured questionnaire to 537 fitness users across nine private fitness centers in Ho Chi Minh City, Vietnam. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to validate the measurement model and test the proposed relationships. The findings indicate that perceived value serves as a central mechanism explaining intention to use. Specifically, performance expectancy ($\beta = 0.373$, $p = 0.000$), effort expectancy ($\beta = 0.252$, $p = 0.000$), and hedonic motivation ($\beta = 0.179$, $p = 0.000$) positively influence perceived value, whereas perceived cost negatively affects it ($\beta = -0.199$, $p = 0.000$). In addition, facilitating conditions ($\beta = 0.224$, $p = 0.000$) and perceived value ($\beta = 0.313$, $p = 0.000$) positively affect intention to use, while privacy has a significant negative effect ($\beta = -0.186$, $p = 0.000$). By contrast, social influence does not significantly affect intention to use ($\beta = 0.048$, $p = 0.288$). Importantly, EWOM positively moderates the relationship between perceived value and intention to use ($\beta = 0.088$, $p = 0.004$). These findings extend the integrated UTAUT2 and VAM framework to the context of AI fitness coaching in an emerging market and provide practical implications for promoting users' intention to use such services.

Keywords: Mobile fitness applications, Privacy, Perceived value, VAM, Electronic Word-of-Mouth, Artificial intelligence (AI)

Introduction

The rapid advancement of artificial intelligence (AI) over the past decade has played a transformative role in reshaping how users interact with digital technologies, particularly in systems that adapt and influence user behavior based on individual data inputs (Rosário et al., 2025; Rai et al., 2019). Supported by major developments in computer science and large-scale data processing, AI applications are increasingly capable of collecting, analyzing, and predicting user behavior in real time (LeCun et al., 2015; Majumder and Deen, 2019; Dwivedi et al., 2021). These capabilities allow AI systems to deliver personalized solutions and develop a deeper understanding of user needs and preferences (Davenport et al., 2020).

In the domain of sports and fitness, the integration of AI has accelerated the emergence of AI fitness coaching, which refers to digital coaching systems that adapt training programs based on individual physiological data and behavioral patterns (Maher et al., 2020; Singh et al., 2023). Within this context, AI fitness coaching can be defined as an AI-based application that promotes physical activity and improves health-related behaviors by assisting users in designing effective training plans and enhancing overall health outcomes (Maher et al., 2020). These systems are also capable of supporting personalized nutrition planning based on users' specific needs.

Recent studies indicate that AI coaching systems can tailor training programs to individual users and dynamically adjust training intensity based on continuously monitored health data (op den Akker et al., 2015). Through ongoing feedback and adaptive interaction, these systems contribute to sustaining long-term user engagement and continued intention to use. Following the COVID-19 pandemic, global levels of physical activity declined significantly while home-based exercise behaviors increased sharply, positioning digital coaching solutions as an important tool for maintaining physical health (Yeung et al., 2024). In this broader context, fitness technologies are increasingly recognized for their role in enhancing movement skills, physical fitness, and overall quality of life while promoting a healthy lifestyle (Rybalko et al., 2024). As a result, AI fitness coaching has been increasingly integrated into health and fitness services, including conversational agents that support workout planning and intelligent assistants that monitor user behavior in real time (Tropea et al.,

2019; Klasnja et al., 2019). However, despite its rapid growth, the widespread availability of AI fitness coaching does not necessarily ensure users' intention to use or continued engagement. Despite this growing interest, prior research has not yet provided a sufficiently integrated explanation of users' intention to use AI fitness coaching, particularly in emerging-market settings such as Vietnam.

Understanding the determinants of users' intention to use AI fitness coaching has therefore become a critical issue in both academic research and practical applications. In the field of technology adoption, the Unified Theory of Acceptance and Use of Technology and its extended version are widely recognized as influential frameworks for explaining behavioral intention and technology usage behavior (Venkatesh et al., 2003; Venkatesh et al., 2012). In the present study, selected constructs from UTAUT2, namely performance expectancy, effort expectancy, hedonic motivation, social influence, and facilitating conditions, are employed to capture technology-related beliefs and usage conditions relevant to AI fitness coaching.

In parallel, the Value-based Adoption Model (VAM) emphasizes that users evaluate a technology based on whether its perceived benefits outweigh its associated sacrifices (Hsiao and Chen, 2016). According to this model, perceived value is formed through a trade-off between perceived benefits and perceived sacrifices. Integrating selected UTAUT2 constructs with VAM provides a more comprehensive explanation of intention to use, as the former captures technology-related beliefs and enabling conditions, whereas the latter explains how users translate these evaluations into perceived value and behavioral intention. In digital health service contexts, perceived value has been consistently identified as a strong predictor of intention to use (Yang et al., 2016; Shaw and Sergueeva, 2019).

In the context of AI fitness coaching, perceived value is likely to be shaped by both functional benefits, such as improved training effectiveness and performance optimization, and experiential benefits associated with user engagement. At the same time, perceived value is influenced by perceived cost and the effort required to use the system. Previous studies suggest that virtual coaching programs can enhance users' physical activity levels, improve dietary behaviors, and positively affect health indicators, while also enriching user experience through interactive and multimodal interfaces (Maher et al., 2020). Moreover, users in digital environments are increasingly influenced by electronic word-of-mouth (EWOM), which serves as an important source of information in shaping attitudes and behavioral intentions. Prior research suggests that EWOM can moderate the relationship between perceived value and intention to use by strengthening the effect of positive evaluations (Erkan and Evans, 2016; Wang et al., 2018). For example, Liao et al. (2022) demonstrate that higher levels of positive EWOM significantly amplify the influence of perceived value on intention to use. However, empirical evidence regarding the moderating role of EWOM remains limited and has primarily been examined in specific digital marketing contexts. In addition, earlier studies have often treated EWOM as a direct antecedent of behavioral intention rather than examining its moderating effect (Erkan and Evans, 2016).

Another critical issue in AI-based services is privacy. Since AI fitness coaching applications require the collection and processing of personal data related to health and behavioral activities, privacy concerns may act as a significant barrier to intention to use (Dinev et al., 2006). Research in digital services indicates that higher perceived risk of data misuse reduces users' willingness to use technology (Baruh et al., 2017). Despite its importance, privacy has not been sufficiently incorporated into research models examining AI fitness coaching in fitness contexts. The existing literature reveals three important gaps. First, empirical evidence on users' intention to use AI fitness coaching remains limited, particularly in emerging markets such as Vietnam. Second, few studies have integrated selected UTAUT2 constructs with VAM to explain how perceived value is formed and how it translates into intention to use in this context. Third, the roles of privacy as a direct barrier and EWOM as a moderating condition remain underexplored in AI fitness coaching research.

To address these research gaps, this study aims to investigate the mechanisms underlying users' intention to use AI fitness coaching in Vietnam. Specifically, perceived value is positioned as a central construct influenced by performance expectancy, hedonic motivation, effort expectancy, and perceived cost. The study also examines the direct effects of social influence, facilitating conditions, and privacy on intention to use. In addition, EWOM is examined as a contextual factor that may strengthen the relationship between perceived value and intention to use.

The specific research objectives are as follows:

- To examine the effects of performance expectancy, hedonic motivation, effort expectancy, and perceived cost on perceived value.
- To analyze the effects of social influence, facilitating conditions, perceived value, and privacy on users' intention to use AI fitness coaching.
- To investigate the moderating role of electronic word-of-mouth in the relationship between perceived value and intention to use.

This study contributes to the literature by offering an integrated explanation of users' intention to use AI fitness coaching, extending selected UTAUT2 constructs and VAM to an emerging-market fitness context, and clarifying the roles of privacy and EWOM in shaping user responses. The findings are expected to advance understanding of consumer behavior in AI-driven fitness services in emerging markets and provide practical implications for enhancing perceived value, managing privacy-related risks, and leveraging EWOM to strengthen users' intention to use AI fitness coaching.

Material & methods

Research Model

Performance Expectancy (PE) is defined as the degree to which an individual believes that using technology will provide benefits and help improve performance and outcomes in carrying out specific activities (Venkatesh et al., 2003). PE is often regarded as the most influential determinant of users' attitudes and intentions, as it directly reflects the functional benefits and utilities delivered by technology (Van der Merwe and Terblanche, 2025; Camilleri, 2024; Leong et al., 2021). When users perceive that technological devices assist them in planning and improving performance, thereby enhancing perceived performance benefits, this forms the basis for higher perceived value and subsequently promotes adoption intention (Dindorf et al., 2025; Wang et al., 2020). Accordingly, the study proposes the following hypothesis:

H1: *Performance expectancy positively influences perceived value.*

Hedonic motivation (HM) refers to the degree of enjoyment and pleasure that users experience when interacting with and using technology (Wu et al., 2025). Beyond providing immediate enjoyment, hedonic motivation may also enhance users' perceptions of the benefits associated with technology use (El-Gayar & Elnoshokaty, 2023). Therefore, hedonic motivation significantly influences perceived value and affects users' acceptance and use of AI coaching (Acosta-Enriquez et al., 2024). Accordingly, the study proposes the following hypothesis:

H2: *Hedonic motivation positively influences perceived value.*

Effort Expectancy (EE) reflects users' perception of the ease of using technology (Venkatesh et al., 2003) and plays a critical role in shaping users' attitudes toward technology (Kim et al., 2024). In the context of the video streaming market in China, prior research indicates that effort expectancy directly affects users' perceived value. Moreover, when a technology provides essential functionalities, users are willing to exert greater effort to use it (Wu et al., 2025). This can be explained by the fact that when users perceive a platform or device as easy to use, they tend to evaluate its perceived value more positively (Yang et al., 2016). Accordingly, the study proposes the following hypothesis:

H3: *Effort expectancy positively influences perceived value.*

Perceived cost (PC) is formed through a trade-off between perceived benefits and monetary cost. Therefore, as perceived cost increases, the perceived value of technology decreases (Kim et al., 2007). Empirical evidence in mHealth contexts also confirms that cost burdens act as practical barriers, reducing service attractiveness (Alam et al., 2021; Niyomyart et al., 2024). In online content services, perceived cost has been shown to exert a strong negative impact on perceived value (Wang et al., 2013). Across multiple domains including mobile telecommunications, digital content, online education, and mHealth, a consistent conclusion emerges: higher perceived sacrifices lead to lower perceived value, thereby reducing the likelihood of adoption and intention to use. Accordingly, the study proposes the following hypothesis:

H4: *Perceived cost negatively influences perceived value.*

Social influence (SI) in digital consumption contexts refers to the degree to which individuals perceive that important others expect or encourage them to use a technology, and it is considered a key antecedent of intention to use in modern adoption models (Venkatesh et al., 2012). Prior studies show that social influence is positively associated with intention to use, although its strength may vary across contexts and user groups (King and He, 2006; Schepers et al., 2007; Williams et al., 2015). This suggests that when individuals receive approval from significant others or observe others using a technology, their intention to use it increases significantly (Martins et al., 2014; Alalwan et al., 2017; Chuah et al., 2016). Accordingly, the study proposes the following hypothesis:

H5: *Social influence positively influences users' intention to use AI fitness coaching.*

Facilitating conditions (FC) reflect users' perceptions of the resources and support available to enable effective use of technology (Venkatesh et al., 2003). Studies of digital health services have found that facilitating conditions positively influence intention to use, as users are more willing to adopt these services when adequate resources, support, and cross-device compatibility are available (Schomakers et al., 2022; Yeung et al., 2024). Similarly, in other contexts such as banking and e-government services, facilitating conditions are identified as a key determinant of users' intention to use (Dwivedi et al., 2019; Baptista and Oliveira, 2017). Accordingly, the study proposes the following hypothesis:

H6: *Facilitating conditions positively influence users' intention to use AI fitness coaching.*

Privacy concerns have emerged as a critical issue in digital environments, particularly in AI-driven services that require extensive personal data (Nunes et al., 2022; Meier et al., 2025). Despite significant privacy concerns, many users of social media and online services still disclose substantial sensitive information and engage only minimally in privacy-protective behaviors if even small personal benefits are involved (Goldfarb and Que, 2023; Li et al., 2012). While users often express concerns about privacy, their actual behavior may not always align with these concerns, a phenomenon known as the privacy paradox (Norberg et al., 2007). However, growing evidence suggests that privacy concerns can significantly influence users' decision-making processes. Users may avoid or limit their engagement with technologies perceived as intrusive or risky (Baruh et al., 2017). Conversely, some studies indicate that users are willing to pay a premium for privacy-protective services (Tsai et

al., 2011), highlighting the importance of privacy in value assessment and behavioral intention. Overall, heightened privacy concerns are expected to reduce users' willingness to adopt AI coaching technologies.

H7: *Privacy negatively influences users' intention to use AI fitness coaching.*

Perceived value (PV) is conceptualized as the overall assessment of utility based on the trade-off between perceived benefits and sacrifices (Zeithaml, 1988). It is widely recognized as a key predictor of consumer decision-making behavior (Jin et al., 2015). Extensive empirical research across various industries, including streaming services, retail, and mobile applications, confirms that perceived value has a strong positive impact on behavioral intention (Kim et al., 2007; Swait and Sweeney, 2000). When users perceive higher value from a service, they are more likely to adopt and continue using it. In the context of AI coaching, perceived value serves as a central mechanism translating users' evaluations into intention to use.

H8: *Perceived value positively influences users' intention to use AI fitness coaching.*

The concept of word-of-mouth (WOM) has long been defined as communication occurring within personal networks (Brooks, 1957), such as recommendations from friends and relatives, primarily through verbal or written communication (Babić Rosario et al., 2020). EWOM refers to consumers' online sharing of experiences, opinions, and evaluations regarding products and services (Hennig-Thurau et al., 2004). With the proliferation of social media and digital platforms, EWOM has become a critical information source influencing consumer decisions (Chen and Yuan, 2020). EWOM not only directly affects behavioral intention but also moderates the relationship between perceived value and intention. Positive EWOM can reinforce users' confidence in their value assessments, thereby strengthening the impact of perceived value on intention (Wang et al., 2018). Similarly, in e-learning contexts, higher levels of EWOM have been shown to amplify the influence of perceived value on intention to use (Liao et al., 2022). Therefore, EWOM is expected to enhance the effect of perceived value on AI coaching adoption.

H9: *Electronic word-of-mouth positively moderates the relationship between perceived value and users' intention to use AI fitness coaching.*

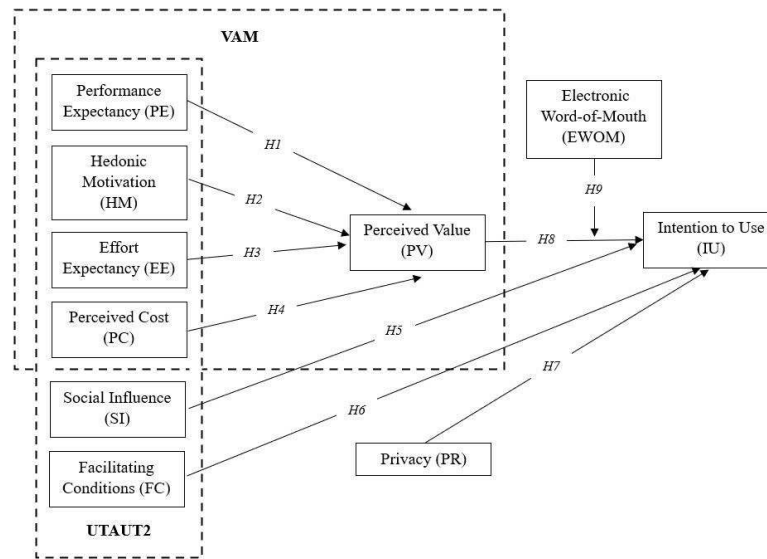


Fig 1. Hypothesized model.

Research Instruments

The measurement scales were developed based on prior studies and adapted to fit the research context. Specifically, the scales for performance expectancy, hedonic motivation, effort expectancy, social influence, facilitating conditions, and intention to use were adapted from Venkatesh et al. (2012). The scale for perceived cost was adapted from Yu (2012). In addition, the electronic word-of-mouth scale was adapted from Sun et al. (2006), while the scale for privacy was adapted from Chellappa and Sin (2005). Finally, the perceived value scale was adapted from Sirdeshmukh et al. (2002). All responses were measured using a 5-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree").

Data collection and sample

This study focuses on fitness users across nine private fitness centers in Ho Chi Minh City, where the demand for health and fitness services is high and user participation is substantial. Given the accessibility of active fitness users and the exploratory nature of the study, a convenience sampling approach was employed across the selected fitness centers. Data were collected directly on-site using a structured questionnaire administered to fitness users. Before completing the survey, participants were informed of the purpose of the study and invited to participate voluntarily. A total of 613 questionnaires were distributed. After data screening, 76 responses were excluded due to incomplete or invalid information, resulting in 537 valid questionnaires for

subsequent analysis and hypothesis testing, with a usable response rate of 87.6%. Data collection took place from December 2025 to early March 2026.

As shown in Table 1, the sample was predominantly male (61.6%), while females accounted for 38.4% of respondents. In terms of age, the largest proportion of participants was in the 21–30 age group (34.8%), followed by those under 21 (25.5%) and those aged 31–40 (19.7%). Smaller shares were observed among respondents aged 41–50 (12.7%) and above 50 (7.3%). Regarding monthly income, the sample was relatively distributed across income groups, with the largest share earning less than 10 million VND per month (28.5%), followed by those earning 21–30 million VND (25.7%) and 10–20 million VND (23.6%). Participants with monthly incomes of 31–40 million VND and over 40 million VND represented 13.8% and 8.4%, respectively. Finally, in terms of workout frequency, most respondents reported exercising three to four times per week (46.6%), followed by one to two times per week (29.6%), while 23.8% reported working out more than four times per week.

Table 1. Respondent demographics (N = 537)

Categories		Frequency	Valid Percent (%)
Gender	Male	331	61.6
	Female	206	38.4
Age	Under 21	137	25.5
	21–30	187	34.8
	31–40	106	19.7
	41–50	68	12.7
	Above 50	39	7.3
	Less than 10	153	28.5
Monthly Income (million VND)	From 10 to 20	127	23.6
	From 21 to 30	138	25.7
	From 31 to 40	74	13.8
	Over 40	45	8.4
Workout frequency (times per week)	1–2	159	29.6
	3–4	250	46.6
	More than 4	128	23.8

Results

Measurement model analysis

Table 2 presents the measurement model assessment results, including Cronbach's alpha, rho_A, composite reliability, and average variance extracted (AVE). The findings show that all constructs exhibit satisfactory internal consistency reliability, with Cronbach's alpha ranging from 0.793 to 0.878, rho_A from 0.806 to 0.879, and composite reliability from 0.878 to 0.925, all of which exceed the recommended threshold of 0.70. Convergent validity is also established, as all AVE values range from 0.705 to 0.804, surpassing the recommended minimum of 0.50. To assess discriminant validity, this study employed the heterotrait-monotrait ratio (HTMT). As shown in Table 3, all HTMT values fall below the conservative threshold of 0.85, supporting adequate discriminant validity among the constructs. The highest HTMT value is observed between PE and PV (0.844), followed by EWOM and SI (0.814); however, both remain within the acceptable range. Therefore, the measurement model can be considered reliable and valid, with the constructs demonstrating sufficient empirical distinctiveness for subsequent structural analysis.

Table 2. Construct reliability and convergent validity

	Cronbach's Alpha	rho_A	CR	AVE
EE	0.864	0.868	0.917	0.786
EWOM	0.869	0.871	0.920	0.793
FC	0.847	0.852	0.907	0.765
HM	0.870	0.871	0.920	0.794
IU	0.848	0.848	0.908	0.767
PC	0.878	0.879	0.925	0.804
PE	0.827	0.827	0.896	0.743
PV	0.858	0.859	0.914	0.779
PR	0.793	0.806	0.878	0.705
SI	0.860	0.860	0.914	0.781

Notes. PC = Perceived Cost; PV = Perceived Value; PE = Performance Expectancy; EE = Effort Expectancy; PR = Privacy; EWOM = Electronic Word-of-Mouth; IU = Intention to Use; FC = Facilitating Conditions; HM = Hedonic Motivation; SI = Social Influence.

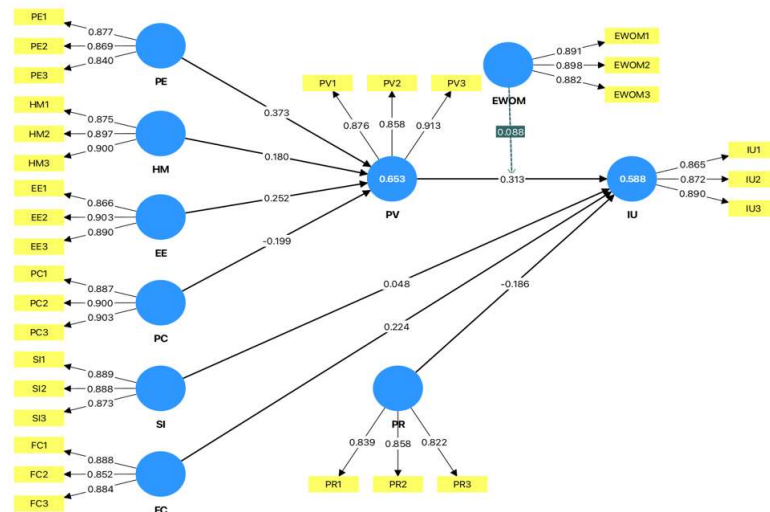
Table 3. Results of discriminant validity using HTMT.

	EE	EWOM	FC	HM	IU	PC	PE	PV	PR	SI
EE										
EWOM	0.448									
FC	0.541	0.445								
HM	0.682	0.495	0.527							
IU	0.531	0.714	0.617	0.519						
PC	0.477	0.380	0.367	0.494	0.483					
PE	0.635	0.509	0.437	0.711	0.518	0.546				
PV	0.746	0.499	0.471	0.741	0.680	0.641	0.844			
PR	0.303	0.269	0.235	0.324	0.441	0.116	0.223	0.232		
SI	0.478	0.814	0.432	0.499	0.623	0.390	0.476	0.481	0.305	
EWOM x PV	0.215	0.070	0.053	0.239	0.035	0.134	0.259	0.210	0.136	0.066

Notes. PC = Perceived Cost; PV = Perceived Value; PE = Performance Expectancy; EE = Effort Expectancy; PR = Privacy; EWOM = Electronic Word-of-Mouth; IU = Intention to Use; FC = Facilitating Conditions; HM = Hedonic Motivation; SI = Social Influence.

Results of hypothesis testing

As presented in Table 4 and illustrated in Figs. 2 and 3, the structural model assessment offers meaningful insights into the proposed relationships among the study constructs, revealing the key drivers of perceived value and intention to use, as well as the moderating role of electronic word-of-mouth. Bootstrapping analysis was performed to examine the significance of the hypothesized relationships. As shown in Table 4, eight of the nine hypotheses are supported. PE ($\beta = 0.373$, $p = 0.000$), HM ($\beta = 0.179$, $p = 0.000$), and EE ($\beta = 0.252$, $p = 0.000$) significantly and positively affect PV, whereas PC negatively affects PV ($\beta = -0.199$, $p = 0.000$). With regard to IU, FC ($\beta = 0.224$, $p = 0.000$) and PV ($\beta = 0.313$, $p = 0.000$) have significant positive effects, while PR has a significant negative effect ($\beta = -0.186$, $p = 0.000$). By contrast, SI does not significantly influence IU ($\beta = 0.048$, $p = 0.288$), leading to the rejection of H5. Moreover, the moderating effect of EWOM on the relationship between PV and IU is positive and statistically significant ($\beta = 0.088$, $p = 0.004$), thus supporting H9. These results highlight that intention to use AI fitness coaching is primarily shaped by perceived value and facilitating conditions, while EWOM serves as an important boundary condition that strengthens the effect of perceived value on intention to use.

**Fig 2. The SmartPLS results.****Table 4. Bootstrapping results.**

Hypotheses	Path coefficients	T-Statistics	Standard Deviation	P-values	Results
H1. PE → PV	0.373	10.195	0.037	0.000	Supported
H2. HM → PV	0.179	4.570	0.039	0.000	Supported
H3. EE → PV	0.252	7.060	0.036	0.000	Supported
H4. PC → PV	-0.199	5.849	0.034	0.000	Supported
H5. SI → IU	0.048	1.062	0.045	0.288	Not supported
H6. FC → IU	0.224	6.705	0.033	0.000	Supported
H7. PR → IU	-0.186	6.239	0.030	0.000	Supported
H8. PV → IU	0.313	9.428	0.033	0.000	Supported
H9. EWOM × PV → IU	0.088	2.914	0.030	0.004	Supported

Notes. PC = Perceived Cost; PV = Perceived Value; PE = Performance Expectancy; EE = Effort Expectancy; PR = Privacy; EWOM = Electronic Word-of-Mouth; IU = Intention to Use; FC = Facilitating Conditions; HM = Hedonic Motivation; SI = Social Influence.

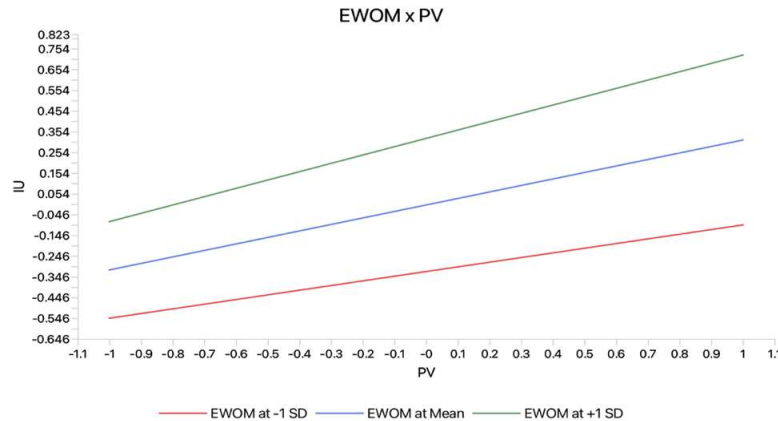


Fig 3. Moderating effect of EWOM on the PV—IU relationship.

Discussion

Determinants of Perceived Value

The findings confirm that performance expectancy has a positive effect on perceived value, indicating that users evaluate AI fitness coaching more favorably when they believe that the system enhances training effectiveness and supports goal achievement. This result is consistent with prior studies showing that improved health-related outcomes, such as increased physical activity, weight reduction, and better fitness levels, enhance perceived value and encourage continued use of technology-supported services (Wang et al., 2020). The results further show that hedonic motivation and effort expectancy positively influence perceived value. Specifically, hedonic motivation enhances users' interest and positive emotional responses, whereas effort expectancy reduces cognitive burden and improves their overall evaluation of the service. This finding is consistent with Liao et al. (2022), who emphasize that hedonic motivation is an important predictor of perceived value, particularly for applications that need to sustain user interest over time. This result is consistent with Venkatesh et al. (2012), Schomakers et al. (2022), and Yeung et al. (2024). This issue is particularly relevant in Vietnam, where differences in digital literacy may shape users' interactions with advanced technologies. Finally, perceived cost negatively influences perceived value, confirming that users' value evaluations decline when financial, temporal, or psychological sacrifices outweigh expected benefits. This result is consistent with previous studies showing that perceived cost reduces perceived value when users view a service as expensive or not commensurate with its benefits (Yang et al., 2016; Venkatesh et al., 2012). This finding also supports the value-based view that perceived value reflects a comparison between benefits and sacrifices (Sánchez-Fernández & Iniesta-Bonillo, 2007; Le et al., 2025). In the context of AI fitness coaching, these costs may include subscription fees, premium upgrades, and time investment, all of which can reduce perceived value when they are considered too high relative to the benefits received.

Determinants of Intention to Use

The findings show that social influence does not have a significant effect on intention to use AI fitness coaching. This result differs from prior studies suggesting that encouragement from family members, friends, and professionals can motivate the adoption of AI-based solutions (Schomakers et al., 2022; Venkatesh et al., 2012; Dwivedi et al., 2019). In this context, adoption appears to be driven less by referent opinions and more by individual assessment of the technology's practical benefits. By contrast, facilitating conditions positively affect intention to use, consistent with evidence that compatible devices, stable internet connectivity, and clear system guidance facilitate technology adoption in emerging digital contexts (Yeung et al., 2024; Dwivedi et al., 2019). In Vietnam, where AI-based fitness services are still relatively new, reducing technical barriers may be essential for promoting user adoption. The results also reveal that privacy negatively affects intention to use, confirming that privacy-related risks remain a major barrier to the adoption of digital health technologies. Consistent with previous research, concerns about data leakage, misuse of personal information, and third-party data sharing may discourage adoption because AI fitness coaching often requires personal health and lifestyle data, even when the service offers substantial functional benefits (Esmaeilzadeh, 2019; Gruzdt et al., 2018; He et al., 2019). Finally, perceived value has a positive and significant effect on intention to use, supporting the value-based view that adoption decisions are shaped by users' evaluation of benefits relative to sacrifices (Zeithaml, 1988; Sánchez-Fernández and Iniesta-Bonillo, 2007). In AI fitness coaching, users are therefore more likely to intend to use the service when its benefits justify the required time and financial investment, broadly consistent with research on the continued use of digital health applications (Alam et al., 2020).

The moderating role of Electronic Word-of-Mouth

The findings indicate that EWOM has a positive moderating effect on the relationship between perceived value and intention to use AI fitness coaching. Specifically, when users are exposed to positive online reviews, feedback, and shared experiences regarding AI fitness coaching, their confidence in the benefits of the service is reinforced, thereby strengthening the effect of perceived value on intention to use. In other words, under favorable EWOM conditions, users not only perceive the service as more valuable but are also more likely to translate that value perception into a stronger intention to use it. This finding is consistent with prior studies in e-commerce and green marketing, which show that EWOM not only directly influences behavioral intention but also amplifies the effect of perceived value on customer attitudes and behaviors (Erkan and Evans, 2016; Wang et al., 2018; Liao et al., 2022). Therefore, in the context of AI fitness coaching, EWOM can be considered an important contextual condition that strengthens the relationship between perceived value and intention to use.

Conclusions

This study integrates UTAUT2 and the Value-based Adoption Model (VAM) to explain users' intention to use AI fitness coaching in Vietnam. The findings confirm that perceived value is the most important mechanism driving intention to use. Specifically, perceived value is strengthened by performance expectancy, hedonic motivation, and effort expectancy, but weakened by perceived cost. The results further show that facilitating conditions support intention to use, while privacy concerns remain a major barrier. This highlights the importance of technical readiness, device compatibility, user support, and transparent data protection practices in encouraging the use of AI fitness coaching. In addition, perceived value has a strong positive direct effect on intention to use, indicating that users are more willing to use AI fitness coaching when they believe its benefits outweigh the associated costs and risks. EWOM also positively moderates the relationship between perceived value and intention to use, suggesting that favorable online reviews, shared experiences, and user feedback strengthen the translation of value perceptions into intention to use. The study contributes to the literature by extending the application of UTAUT2 and VAM to AI-based fitness services in an emerging market context and by demonstrating the important role of EWOM in strengthening intention to use. From a managerial perspective, service providers should improve functional performance, create engaging user experiences, simplify system use, offer flexible pricing, strengthen technical support, ensure privacy protection, and actively encourage positive EWOM.

Despite these contributions, the study has several limitations. First, the reliance on a cross-sectional methodology captures only a single, static snapshot of users' perceptions. This approach is insufficient for tracking how user evaluations may evolve over time, particularly as perceived value, engagement, and satisfaction may change after the initial novelty of AI fitness coaching declines. A longitudinal design is therefore needed to better understand these dynamic changes and their influence on continued intention to use and actual usage behavior. Second, the use of convenience sampling across nine private fitness centers in Ho Chi Minh City may limit the generalizability of the findings. Future research should employ more diverse samples across different regions and types of fitness facilities and explore additional moderating factors such as AI literacy, health consciousness, and trust in technology providers.

Declaration of generative AI and AI-assisted technologies in the writing process: During the preparation of this manuscript, AI-assisted technologies were used to enhance the clarity, flow, and readability of the text. These tools were employed solely for language refinement, including grammar, sentence structure, and overall coherence. The authors reviewed the final manuscript and takes full responsibility for the content of the publication.

Conflicts of interest: The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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References

- Acosta-Enriquez, B. G., Farroñan, E. V. R., Zapata, L. I. V., Garcia, F. S. M., Rabanal-León, H. C., Angaspilco, J. E. M., & Bocanegra, J. C. S. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, 10(19). <https://doi.org/10.1016/j.heliyon.2024.e38315>
- Alalwan, A. A., Rana, N. P., Dwivedi, Y. K., & Algharabat, R. (2017). Social media in marketing: A review and analysis of the existing literature. *Telematics and Informatics*, 34(7), 1177–1190. <https://doi.org/10.1016/j.tele.2017.05.008>
- Alam, M. M. D., Alam, M. Z., Rahman, S. A., & Taghizadeh, S. K. (2021). Factors influencing mHealth adoption and its impact on mental well-being during COVID-19 pandemic: A SEM-ANN approach. *Journal of Biomedical Informatics*, 116, 103722. <https://doi.org/10.1016/j.jbi.2021.103722>
- Alam, M. Z., Hoque, M. R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. *International Journal of Information Management*, 50, 128–143. <https://doi.org/10.1016/j.ijinfomgt.2019.04.016>

- Babić Rosario, A., De Valck, K., & Sotgiu, F. (2020). Conceptualizing the electronic word-of-mouth process: What we know and need to know about eWOM creation, exposure, and evaluation. *Journal of the Academy of Marketing Science*, 48(3), 422–448. <https://doi.org/10.1007/s11747-019-00706-1>
- Baptista, G., & Oliveira, T. (2017). Why so serious? Gamification impact in the acceptance of mobile banking services. *Internet Research*, 27(1), 118–139. <https://doi.org/10.1108/IntR-10-2015-0295>
- Baruh, L., Secinti, E., & Cemalcilar, Z. (2017). Online privacy concerns and privacy management: A meta-analytical review. *Journal of Communication*, 67(1), 26–53. <https://doi.org/10.1111/jcom.12276>
- Brooks Jr., R. C. (1957). “Word-of-mouth” advertising in selling new products. *Journal of Marketing*, 22(2), 154–161. <https://doi.org/10.1177/002224295702200205>
- Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, 201, 123247. <https://doi.org/10.1016/j.techfore.2024.123247>
- Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer’s dilemma. *Information Technology and Management*, 6(2), 181–202. <https://doi.org/10.1007/s10799-005-5879-y>
- Chen, Z., & Yuan, M. (2020). Psychology of word of mouth marketing. *Current Opinion in Psychology*, 31, 7–10. <https://doi.org/10.1016/j.copsyc.2019.06.010>
- Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior*, 65, 276–284. <https://doi.org/10.1016/j.chb.2016.07.047>
- Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, 48(1), 24–42. <https://doi.org/10.1007/s11747-019-00696-0>
- Dindorf, C., Dully, J., Bartaguis, E., Menges, T., Reidick, C., Seibert, J. N., & Fröhlich, M. (2025). Characteristics and perceived suitability of artificial intelligence-driven sports coaches: A pilot study on psychological and perceptual factors. *Frontiers in Sports and Active Living*, 7, 1548980. <https://doi.org/10.3389/fspor.2025.1548980>
- Dinev, T., Bellotto, M., Hart, P., Russo, V., Serra, I., & Colautti, C. (2006). Privacy calculus model in e-commerce: A study of Italy and the United States. *European Journal of Information Systems*, 15(4), 389–402. <https://doi.org/10.1057/palgrave.ejis.3000590>
- Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, 21(3), 719–734. <https://doi.org/10.1007/s10796-017-9774-y>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- El-Gayar, O., & Elnoshokaty, A. (2023). Factors and design features influencing the continued use of wearable devices. *Journal of Healthcare Informatics Research*, 7(3), 359–385. <https://doi.org/10.1007/s41666-023-00135-4>
- Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers’ purchase intentions: An extended approach to information adoption. *Computers in Human Behavior*, 61, 47–55. <https://doi.org/10.1016/j.chb.2016.03.003>
- Esmailzadeh, P. (2019). The impacts of the perceived transparency of privacy policies and trust in providers for building trust in health information exchange: Empirical study. *JMIR Medical Informatics*, 7(4), e14050. <https://doi.org/10.2196/14050>
- Goldfarb, A., & Que, V. F. (2023). The economics of digital privacy. *Annual Review of Economics*, 15, 267–286. <https://doi.org/10.1146/annurev-economics-082322-014346>
- Gruzd, A., & Hernández-García, Á. (2018). Privacy concerns and self-disclosure in private and public uses of social media. *Cyberpsychology, Behavior, and Social Networking*, 21(7), 418–428. <https://doi.org/10.1089/cyber.2017.0709>
- He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine*, 25(1), 30–36. <https://doi.org/10.1038/s41591-018-0307-0>
- Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, 18(1), 38–52. <https://doi.org/10.1002/dir.10073>
- Hsiao, K. L., & Chen, C. C. (2016). What drives in-app purchase intention for mobile games? An examination of perceived values and loyalty. *Electronic Commerce Research and Applications*, 16, 18–29. <https://doi.org/10.1016/j.elerap.2016.01.001>

- Jin, N., Lee, S., & Lee, H. (2015). The effect of experience quality on perceived value, satisfaction, image and behavioral intention of water park patrons: New versus repeat visitors. *International Journal of Tourism Research*, 17(1), 82–95. <https://doi.org/10.1002/jtr.1968>
- Kim, H. W., Chan, H. C., & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. *Decision Support Systems*, 43(1), 111–126. <https://doi.org/10.1016/j.dss.2005.05.009>
- Kim, S., Zhong, Y., Wang, J., & Kim, H. S. (2024). Exploring technology acceptance of healthcare devices: The moderating role of device type and generation. *Sensors*, 24(24), 7921. <https://doi.org/10.3390/s24247921>
- King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, 43(6), 740–755. <https://doi.org/10.1016/j.im.2006.05.003>
- Klasnja, P., Smith, S., Seewald, N. J., Lee, A., Hall, K., Luers, B., ... Murphy, S. A. (2019). Efficacy of contextually tailored suggestions for physical activity: A micro-randomized optimization trial of HeartSteps. *Annals of Behavioral Medicine*, 53(6), 573–582. <https://doi.org/10.1093/abm/kay067>
- Le, T. P., Ngo, S. L., Chau, V. H., & Pham, D. K. (2025). Understanding customer loyalty in sports facilities: Insights into service quality, perceived value, satisfaction and facility image. *Journal of Physical Education and Sport*, 25(1), 71–78. <https://doi.org/10.7752/jpes.2025.01009>
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>
- Leong, M. Y., Kwan, J. H., & Ming, L. M. (2021). Technology readiness and UTAUT2 in e-wallet adoption in a developing country. *F1000Research*, 10, 863. <https://doi.org/10.12688/f1000research.72821.1>
- Li, T., & Unger, T. (2012). Willing to pay for quality personalization? Trade-off between quality and privacy. *European Journal of Information Systems*, 21(6), 621–642. <https://doi.org/10.1057/ejis.2012.13>
- Liao, Y. K., Wu, W. Y., Le, T. Q., & Phung, T. T. T. (2022). The integration of the technology acceptance model and value-based adoption model to study the adoption of e-learning: The moderating role of e-WOM. *Sustainability*, 14(2), 815. <https://doi.org/10.3390/su14020815>
- Maher, C. A., Davis, C. R., Curtis, R. G., Short, C. E., & Murphy, K. J. (2020). A physical activity and diet program delivered by artificially intelligent virtual health coach: Proof-of-concept study. *JMIR mHealth and uHealth*, 8(7), e17558. <https://doi.org/10.2196/17558>
- Majumder, S., & Deen, M. J. (2019). Smartphone sensors for health monitoring and diagnosis. *Sensors*, 19(9), 2164. <https://doi.org/10.3390/s19092164>
- Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, 34(1), 1–13. <https://doi.org/10.1016/j.ijinfomgt.2013.06.002>
- Meier, Y., & Bol, N. (2025). Unequal experiences, unequal outcomes? Digital inequalities in experiencing online benefits and privacy harms, mistrust, and self-inhibiting behaviors. *Journal of Computer-Mediated Communication*, 30(5), zmaf016. <https://doi.org/10.1093/jcmc/zmaf016>
- Niyomyart, A., Ruksakulpiwat, S., Benjasirisan, C., Phianhasin, L., Nigussie, K., Thorngthip, S., ... Begashaw, L. (2024). Current status of barriers to mHealth access among patients with stroke and steps toward the digital health era: Systematic review. *JMIR mHealth and uHealth*, 12, e54511. <https://doi.org/10.2196/54511>
- Norberg, P. A., Horne, D. R., & Horne, D. A. (2007). The privacy paradox: Personal information disclosure intentions versus behaviors. *Journal of Consumer Affairs*, 41(1), 100–126. <https://doi.org/10.1111/j.1745-6606.2006.00070.x>
- Nunes, N., Adamo, G., Ribeiro, M., Gouveia, B. R., Gouveia, E. R., Teixeira, P., & Nisi, V. (2022). Modeling adoption, security, and privacy of COVID-19 apps: Findings and recommendations from an empirical study using the unified theory of acceptance and use of technology. *JMIR Human Factors*, 9(3), e35434. <https://doi.org/10.2196/35434>
- op den Akker, H., Cabrita, M., op den Akker, R., Jones, V. M., & Hermens, H. J. (2015). Tailored motivational message generation: A model and practical framework for real-time physical activity coaching. *Journal of Biomedical Informatics*, 55, 104–115. <https://doi.org/10.1016/j.jbi.2015.03.005>
- Rai, A., Constantinides, P., & Sarker, S. (2019). Editor's comments: Next-generation digital platforms: Toward human-AI hybrids. *MIS Quarterly*, 43(1), iii–ix. <https://doi.org/10.25300/MISQ/2019/13781>
- Rosário, A. T., & Raimundo, R. J. (2025). The integration of AI and IoT in marketing: A systematic literature review. *Electronics*, 14(9), 1854. <https://doi.org/10.3390/electronics14091854>
- Rybalko, L., Hulko, T., Yopa, T., Żukow, X., Gorgol, P., Khomenko, E., & Żukow, W. (2024). Using fitness technologies to address post-traumatic stress disorders. *Journal of Physical Education and Sport*, 24(7), 1569–1581. <https://doi.org/10.7752/jpes.2024.07177>
- Sánchez-Fernández, R., & Iniesta-Bonillo, M. Á. (2007). The concept of perceived value: A systematic review of the research. *Marketing Theory*, 7(4), 427–451. <https://doi.org/10.1177/1470593107083165>
- Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information & Management*, 44(1), 90–103. <https://doi.org/10.1016/j.im.2006.10.007>

- Schomakers, E. M., Lidynia, C., Vervier, L. S., Calero Valdez, A., & Ziefle, M. (2022). Applying an extended UTAUT2 model to explain user acceptance of lifestyle and therapy mobile health apps: Survey study. *JMIR mHealth and uHealth*, 10(1), e27095. <https://doi.org/10.2196/27095>
- Shaw, N., & Sergueeva, K. (2019). The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *International Journal of Information Management*, 45, 44–55. <https://doi.org/10.1016/j.ijinfomgt.2018.10.024>
- Singh, B., Olds, T., Brinsley, J., Dumuid, D., Virgara, R., Matricciani, L., ... Maher, C. (2023). Systematic review and meta-analysis of the effectiveness of chatbots on lifestyle behaviours. *NPJ Digital Medicine*, 6(1), 118. <https://doi.org/10.1038/s41746-023-00856-1>
- Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. *Journal of Marketing*, 66(1), 15–37. <https://doi.org/10.1509/jmkg.66.1.15.18449>
- Sun, T., Youn, S., Wu, G., & Kuntaraporn, M. (2006). Online word-of-mouth (or mouse): An exploration of its antecedents and consequences. *Journal of Computer-Mediated Communication*, 11(4), 1104–1127. <https://doi.org/10.1111/j.1083-6101.2006.00393.x>
- Swait, J., & Sweeney, J. C. (2000). Perceived value and its impact on choice behavior in a retail setting. *Journal of Retailing and Consumer Services*, 7(2), 77–88. [https://doi.org/10.1016/S0969-6989\(99\)00012-0](https://doi.org/10.1016/S0969-6989(99)00012-0)
- Tropea, P., Schlieter, H., Sterpi, I., Judica, E., Gand, K., Caprino, M., ... & Corbo, M. (2019). Rehabilitation, the great absentee of virtual coaching in medical care: scoping review. *Journal of Medical Internet Research*, 21(10), e12805. <https://doi.org/10.2196/12805>
- Tsai, J. Y., Egelman, S., Cranor, L., & Acquisti, A. (2011). The effect of online privacy information on purchasing behavior: An experimental study. *Information Systems Research*, 22(2), 254–268. <https://doi.org/10.1287/isre.1090.0260>
- Van der Merwe, H., & Terblanche, N. (2025). Individual propensity to use an AI coaching chatbot in the contact centre environment. *Journal of Work-Applied Management*. <https://doi.org/10.1108/JWAM-03-2025-0046>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>
- Wang, H., Tao, D., Yu, N., & Qu, X. (2020). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. *International Journal of Medical Informatics*, 139, 104156. <https://doi.org/10.1016/j.ijmedinf.2020.104156>
- Wang, J. J., Wang, L. Y., & Wang, M. M. (2018). Understanding the effects of eWOM social ties on purchase intentions: A moderated mediation investigation. *Electronic Commerce Research and Applications*, 28, 54–62. <https://doi.org/10.1016/j.elerap.2018.01.011>
- Wang, Y. S., Yeh, C. H., & Liao, Y. W. (2013). What drives purchase intention in the context of online content services? The moderating role of ethical self-efficacy for online piracy. *International Journal of Information Management*, 33(1), 199–208. <https://doi.org/10.1016/j.ijinfomgt.2012.09.004>
- Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, 28(3), 443–488. <https://doi.org/10.1108/JEIM-09-2014-0088>
- Wu, T., Jiang, N., Sharif, S. P., & Chen, M. (2025). Explaining subscription intention for video streaming platforms in China: Integrating the UTAUT2 model, perceived value theory, and S-O-R theory. *PLoS ONE*, 20(5), e0322860. <https://doi.org/10.1371/journal.pone.0322860>
- Yang, H., Yu, J., Zo, H., & Choi, M. (2016). User acceptance of wearable devices: An extended perspective of perceived value. *Telematics and Informatics*, 33(2), 256–269. <https://doi.org/10.1016/j.tele.2015.08.007>
- Yeung, N. C., Lau, S. T., Mak, W. W. S., Cheng, C. P. S., Chan, E. Y. Y., Siu, J. Y. M., & Cheung, P. S. Y. (2024). Applying the unified theory of acceptance and use of technology to identify factors associated with intention to use teledelivered supportive care among recently diagnosed breast cancer survivors during COVID-19 in Hong Kong: Cross-sectional survey. *JMIR Cancer*, 10(1), e51072. <https://doi.org/10.2196/51072>
- Yu, C. S. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research*, 13(2), 104.
- Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, 52(3), 2–22. <https://doi.org/10.1177/002224298805200302>