E-ISSN: 2708-4523
P-ISSN: 2708-4515
Impact Factor (RJIF): 5.61
AJMC 2026; 7(1): 221-225

www.allcommercejournal.com
Received: 18-10-2025
Accepted: 23-11-2025

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Understanding users intention to use AI coaching in Vietnam's gym context: The role of perceived value

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DOI: https://www.doi.org/10.22271/27084515.2026.v7.i1c.990

Abstract
This study examines users' intention to use AI coaching in the gym context in Vietnam by positioning perceived value as the central explanatory mechanism. Data were collected via a structured, self-administered questionnaire from gym users in Ho Chi Minh City and members of bodybuilding and online fitness communities who had prior experience using an AI Coach (N = 434). All constructs were measured using a five-point Likert scale, and the proposed model was tested using PLS-SEM in SmartPLS. The results show that performance expectancy, hedonic motivation, and effort expectancy positively and significantly influence perceived value, whereas perceived cost negatively affects perceived value. In turn, perceived value has a significant positive effect on intention to use AI coaching. Overall, the findings indicate that adoption intention is primarily driven by users' value perceptions, which are strengthened by perceived benefits, enjoyment, and ease of use, but weakened by cost-related sacrifices.

Keywords: AI coaching, intention to use, VAM

Introduction
Artificial intelligence (AI) has increasingly permeated multiple aspects of society due to advances in cutting-edge technologies that enable systems to observe, collect, and record information, as well as to predict and personalize user behaviors in real time (LeCun *et al*., 2015; Majumder & Deen, 2019) [10, 15]. This development is particularly salient in the health and sport domain, where algorithms can move beyond passive monitoring of physical-activity data to deliver recommendations, reminders, and feedback-functioning as a digital coach that accompanies users throughout their training process.

Within this context, AI coaching has attracted growing attention as a data-driven form of coaching support. Recent studies indicate that AI coaching can assist users in developing training plans, adjusting training intensity based on tracked data, and strengthening the initiation and long-term maintenance of training motivation (Weimann *et al*., 2022; Gabarron *et al*., 2024) [30, 7]. The relevance of AI coaching has become even more pronounced in the post-Covid-19 period, as accumulating evidence suggests that physical activity levels declined substantially, with adverse consequences for health. In parallel, fitness applications have proliferated and increasingly support health-related behaviors through video streaming, gamified elements, and motivational features designed to encourage and sustain physical activity (Ammar *et al*., 2021) [3].

Driven by rapid technological progress over the past decade, AI coaching has expanded from a stand-alone training aid to an integral component of broader interventions that promote physical activity and nutrition. These implementations span diverse forms-from planning-oriented chatbots to virtual assistants integrated with wearable devices-thereby enhancing opportunities for personalization and continuous interaction during use (Maher *et al*., 2020; Tropea *et al*., 2019) [14, 23]. From a user-experience perspective, recent evidence suggests that perceived benefits-particularly usefulness and enjoyment-exert positive and significant effects on the perceived value of such services, while also enhancing convenience, personalization, and users' willingness to act on AI-generated recommendations (Shen *et al*., 2024; Wachholz *et al*., 2025) [19, 27]. This pattern implies that perceived value may represent a central mechanism for explaining why users become willing-or unwilling-to adopt AI coaching in real-world training settings. Nevertheless, existing research continues to leave important gaps regarding AI coaching services.

Much of the literature on usage intention in digital health and sport has focused on applications or smart wearables and has primarily validated UTAUT2 pathways to intention (either directly or via perceived value), whereas evidence specific to AI coaching services remains limited (Schomakers *et al*., 2022; Weimann *et al*., 2022; Maher *et al*., 2020) [18, 30, 14]. Moreover, within the value-based adoption perspective, the negative relationship between perceived cost and perceived value has been supported in contexts such as mobile internet, digital content, and recurring-fee services; however, this relationship has not been directly tested in AI coaching services, where cost structures and the effort required for onboarding and sustained use may operate differently (Kim *et al*., 2007) [9].
Against this background, the present study examines Intention to Use AI Coaching Based on Users' Perceived Value in Vietnam, emphasizing perceived value as a pivotal explanatory mechanism for users' intention to adopt AI coaching. By clarifying how value is formed through perceived benefits and user sacrifices, this study aims to extend empirical evidence in the AI coaching service context and to offer practical implications for the design and implementation of AI coaching in Vietnam.

Materials & Methods

Research Model

Performance expectancy is defined as an individual's belief that using a technology will deliver benefits and help improve achievements and outcomes when performing specific activities (Venkatesh *et al*., 2003) [25]. PE is frequently regarded as one of the most influential determinants of users' attitudes and behavioral intentions because it captures the core benefits and functional advantages provided by the technology (Van der Merwe & Terblanche, 2025; Camilleri, 2024) [24, 4]. When users perceive that technology-enabled devices support planning and enhance performance, their perceived performance benefits increase; this perception provides a basis for forming higher perceived value, which in turn strengthens perceived value and promotes adoption intention (Dindorf *et al*., 2025; Wang *et al*., 2020) [5, 28]. Based on the theoretical arguments above, the following hypothesis is proposed:

H1: The performance expectancy of the AI Coach positively influences perceived value.
Hedonic motivation refers to the extent of enjoyment, pleasure, and intrinsic interest that users experience when interacting with and using a technology (Wu *et al*., 2025) [31]. Moon and Kim (2001) [16] argue that such affective experiences can be reflected through three key components-curiosity, interest, and enjoyment-which collectively attract users to a platform in a positive manner. Accordingly, hedonic motivation is expected to exert a significant influence on users' perceived value, thereby shaping their acceptance and use of artificial intelligence technologies (Acosta-Enriquez *et al*., 2024) [1]. Based on these theoretical arguments, the following hypothesis is proposed:

H2: Hedonic motivation positively influences perceived value.
Effort expectancy refers to users' perceptions of the degree of ease associated with using a technology (Venkatesh *et al*., 2003) [25]. It is a salient factor that shapes users' attitudes toward technology adoption. Moreover, when a technology provides necessary and relevant functionalities, users may be willing to invest greater effort in using it. This can be explained by the notion that when users perceive a platform or device as easy to use, they tend to appraise the experience as more valuable, thereby reporting higher perceived value (Yang *et al*., 2016) [32]. Based on these arguments, the following hypothesis is proposed:

H3: Effort expectancy directly influences perceived value.
Within the Value-based Adoption Model (VAM), perceived value is conceptualized as a trade-off between the benefits obtained and the sacrifices incurred-such as monetary cost, time, or risk. Accordingly, as costs increase, users' perceived value of a technology tends to decrease (Kim *et al*., 2007) [9]. From the UTAUT2 perspective, perceived value (often operationalized as price value) reflects the balance between the benefits received and the monetary costs borne; when costs outweigh benefits, users evaluate the technology as less valuable and become less inclined to adopt it (Venkatesh *et al*., 2012) [26]. Empirical evidence in mHealth similarly indicates that burdens such as subscription fees and device/connectivity expenses constitute tangible barriers that reduce service attractiveness (Alam *et al*., 2021; Niyomyart *et al*., 2024) [2, 17]. In fee-based digital services with recurring payments, prior findings also support this logic: higher cost burdens-especially when combined with greater usage effort-lower users' perceived value, and this perceived value is a key determinant of usage intention. In research on online content services grounded in VAM, monetary cost has been shown to exert a strong negative effect on perceived value. Taken together, evidence across domains-including mobile telecommunications, digital content, online education, and mHealth-converges on a consistent conclusion: greater perceived costs or sacrifices reduce perceived value, thereby lowering the likelihood of adoption and weakening users' intention to use the technology. Therefore, the following hypothesis is proposed:

H4: Perceived cost of AI coaching negatively influences users' perceived value.
The concept of perceived value has attracted substantial scholarly attention and has been extensively examined over the past decades. It is commonly defined as a trade-off between what customers receive and what they give up to obtain a service. Consumer behavior research consistently suggests that consumers' value perceptions toward a product or service constitute one of the most influential determinants of their decision-making behavior (Jin *et al*., 2015) [8]. Evidence from the streaming-services context similarly supports this proposition, indicating that perceived value is a key driver of continuance intention (Singh, 2021) [20]. Across diverse research settings-including retail and mobile technology-prior studies have repeatedly demonstrated that perceived value positively influences consumers' intention to use products and services (Liu *et al*., 2015; Kim, 2007; Swait & Sweeney, 2000) [13, 9, 22]. In general, consumers who perceive higher value are more likely to purchase and use a product or service (Wang, 2019) [29]. Based on these theoretical arguments, the following hypothesis is proposed:

H5: Perceived value positively influences Intention to Use

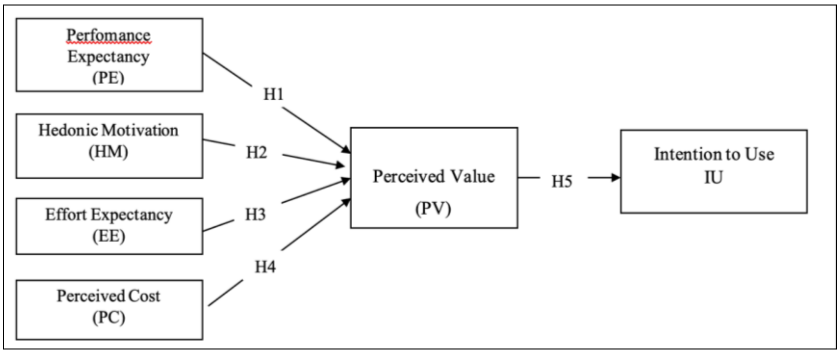

Fig 1: Hypothesized model

Research Instruments

All constructs were measured using a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The research scale was constructed and developed based on pre-existing scales from previous studies, adapted to fit the current research context. The measurement scales were adapted from prior studies, drawing on Venkatesh *et al*. (2012) [26] for performance expectancy, hedonic motivation, effort expectancy, perceived cost, and intention to use, and on Sirdeshmukh *et al*. (2012) for perceived value.

Data collection and sample

In the present study, a quantitative research design was employed to empirically test the proposed hypotheses. Data were collected using a structured, self-administered questionnaire distributed to individuals engaged in gym-based training in Ho Chi Minh City, as well as to members of bodybuilding groups and online fitness communities on social media platforms. Prior to participation, respondents received a clear explanation of the study's purpose and procedures. To ensure sample relevance, a screening question was used to verify whether participants had previously used AI coaching during their training process; only those who met this criterion were invited to complete the full survey. Data collection was conducted from August 2025 to the end of September 2025.

A total of 434 valid questionnaires were retained for subsequent analysis and hypothesis testing. As presented in Table 1, the respondent profile was predominantly female (59.1%), while males accounted for 40.9% of the sample. In terms of age, most participants were 25-35 years old (39.6%), followed by those under 25 (36.7%), whereas respondents over 35 represented 24.0%. Regarding monthly income, the largest proportion reported earnings of 15-20 million VND (30.0%), followed by 10-15 million VND (24.0%) and over 20 million VND (22.1%); smaller shares fell into the 5-10 million VND (15.0%) and under 5 million VND (9.0%) categories. Overall, the sample reflects a relatively young respondent base with moderate-to-upper income levels in the study context.

Table 1: Respondent demographics (N = 434)

Category	Classification	Sample Amounts	Percent (%)
Gender	Male	177	40,9
	Female	256	59,1
Age	Under 25	159	36,7
	25-35	170	39,6
	Over 35	104	24,0
Monthly Income (million VND)	Under 5 million VND	39	9,0
	From 5-10 million VND	65	15,0
	From 10-15 million VND	104	24,0
	From 15-20 million VND	130	30,0
	Over 20 million VND	96	22,1

Results

Empirical Results and Discussions

Based on Table 2, the constructs demonstrate satisfactory internal consistency reliability. Specifically, Cronbach's alpha values range from 0.756 to 0.881, and rho_A values range from 0.759 to 0.882, exceeding the recommended threshold of 0.70 for all constructs (EE, HM, IT, PC, PE, and PV). In addition, composite reliability (CR) values are high (0.859-0.926), further confirming scale reliability. Convergent validity is also supported, as the average variance extracted (AVE) for each construct is above 0.50, ranging from 0.671 to 0.807, indicating that each construct explains a substantial proportion of variance in its indicators.

Discriminant validity was evaluated using the heterotrait-monotrait ratio (HTMT) (Table 3). The HTMT values are consistently low, ranging from 0.042 to 0.433, and all are well below the commonly accepted cut-off values. These results provide strong evidence that the constructs are empirically distinct, confirming adequate discriminant validity for the measurement model.

Table 2: Standardized loading coefficient, Cronbach's α, rho_A, CR, and AVE

	Cronbach's Alpha	rho_A	CR	AVE
EE	0.757	0.759	0.860	0.673
HM	0.815	0.815	0.890	0.730
IU	0.775	0.789	0.868	0.687
PC	0.881	0.882	0.926	0.807
PE	0.756	0.766	0.859	0.671
PV	0.790	0.793	0.877	0.704

Note: PE = Perfomance Expectancy; HM = Hedonic Motivation; EE = Effort Expectancy; PC = Perceived Cost; PV = Perceived Value; IU = Intention to Use

Table 3: Results of discriminant validity using HTMT

	EE	HM	IT	PC	PE	PV
EE						
HM	0.363					
IU	0.359	0.433				
PC	0.096	0.042	0.077			
PE	0.271	0.362	0.235	0.045		
PV	0.394	0.416	0.369	0.178	0.413	

Note: PE = Perfomance Expectancy; HM = Hedonic Motivation; EE = Effort Expectancy; PC = Perceived Cost; PV = Perceived Value; IU = Intention to Use

Table 4: Bootstrapping results

Hypotheses	Path coefficients	T -Statistics	Standard Deviation	P-values	Results
H1. PE → PV	0.216	6.208	0.048	0.000	Supported
H2. HM → PV	0.209	4.392	0.048	0.000	Supported
H3. EE → PV	0.211	4.692	0.045	0.000	Supported
H4. PC → PV	-0.155	4.131	0.037	0.000	Supported
H5. PV → IU	0.295	6.208	0.048	0.000	Supported

Note: PE = Perfomance Expectancy; HM = Hedonic Motivation; EE = Effort Expectancy; PC = Perceived Cost; PV = Perceived Value; IU = Intention to Use

The bootstrapping analysis provides strong support for the proposed structural relationships. The path from PE to PV yields a path coefficient of 0.216 with a p-value of 0.000, confirming the positive influence of performance expectancy on perceived value and thereby supporting H1. This implies that when users believe AI coaching can enhance training effectiveness and outcomes, they are more likely to perceive higher value from the service. Similarly, the path from HM to PV shows a p-value of 0.000 and a path coefficient of 0.209, confirming the effect of hedonic motivation on perceived value and thereby supporting H2. This result suggests that enjoyment and interest experienced during interaction with AI coaching contribute to stronger value perceptions. In addition, the path from EE to PV reports a path coefficient of 0.211 with a p-value of 0.000, confirming the influence of effort expectancy on perceived value and thereby supporting H3. This indicates that when AI coaching is perceived as easy to use, users tend to appraise the service as more valuable. Conversely, the path from PC to PV presents a p-value of 0.000 and a negative path coefficient of −0.155, confirming the adverse impact of perceived cost on perceived value and thereby supporting H4. This finding highlights that higher perceived monetary or non-monetary costs diminish users' value evaluations of AI coaching. Finally, the path from PV to IU demonstrates a path coefficient of 0.295 with a p-value of 0.000, confirming the positive effect of perceived value on intention to use and thereby supporting H5. This underscores the central role of perceived value as a key driver of users' intention to adopt AI coaching in the gym training context.

Conclusion

The findings offer a coherent explanation of intention formation toward AI coaching in the gym context, highlighting perceived value as the pivotal mechanism that translates users' technology-related evaluations into usage intention. Specifically, performance expectancy, hedonic motivation, and effort expectancy each exert significant positive effects on perceived value, indicating that users are more likely to evaluate AI coaching as valuable when it is perceived as beneficial for training outcomes, enjoyable to use, and easy to operate. In contrast, perceived cost significantly reduces perceived value, suggesting that monetary burdens and other perceived sacrifices can erode users' overall value appraisal of AI coaching. Importantly, perceived value shows a strong positive effect on intention to use, underscoring that value perceptions serve as the most proximal driver of adoption intention in this setting. Taken together, the results imply that increasing adoption of AI coaching in Vietnam's fitness market requires not only strengthening users' perceived benefits and user experience, but also managing cost perceptions so that the overall benefit-sacrifice trade-off remains favorable.

While the study advances understanding of AI coaching adoption in Vietnam by emphasizing a value-based mechanism, several limitations should be acknowledged. First, the sample was collected from gym users in Ho Chi Minh City and online fitness communities, which may restrict generalizability to other regions and user segments; future studies should replicate the model across diverse locations and populations. Second, although the model captures core value antecedents and intention, additional factors-such as social influence dynamics in fitness communities, habit formation, or trust in AI recommendations-may further enhance explanatory power.

References

1. Acosta-Enriquez BG, Farroñan EVR, Zapata LIV, Garcia FSM, Rabanal-León HC, Angaspilco JEM, *et al*. Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. Heliyon. 2024;10(19):e38316.
2. Alam MMD, Alam MZ, Rahman SA, Taghizadeh SK. Factors influencing mHealth adoption and its impact on mental well-being during COVID-19 pandemic: A SEM-ANN approach. J Biomed Inform. 2021;116:103722.
3. Ammar A, Trabelsi K, Brach M, Chtourou H, Boukhris O, Masmoudi L, *et al*. Effects of home confinement on mental health and lifestyle behaviours during the COVID-19 outbreak: Insight from the ECLB-COVID19 multicenter study. Biol Sport. 2021;38(1):9-21.
4. Camilleri MA. Factors affecting performance expectancy and intentions to use ChatGPT: Using

SmartPLS to advance an information technology acceptance framework. Technol Forecast Soc Change. 2024;201:123247.
5. Dindorf C, Dully J, Bartaguiz E, Menges T, Reidick C, Seibert JN, *et al*. Characteristics and perceived suitability of artificial intelligence-driven sports coaches: A pilot study on psychological and perceptual factors. Front Sports Act Living. 2025;7:1548980.
6. El-Gayar O, Elnoshokaty A. Factors and design features influencing the continued use of wearable devices. J Healthc Inform Res. 2023;7(3):359-385.
7. Gabarron E, Larbi D, Rivera-Romero O, Denecke K. Human factors in AI-driven digital solutions for increasing physical activity: Scoping review. JMIR Hum Factors. 2024;11:e55964.
8. Jin N, Lee S, Lee H. The effect of experience quality on perceived value, satisfaction, image and behavioral intention of water park patrons: New versus repeat visitors. Int J Tour Res. 2015;17(1):82-95.
9. Kim HW, Chan HC, Gupta S. Value-based adoption of mobile internet: An empirical investigation. Decis Support Syst. 2007;43(1):111-126.
10. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-444.
11. Li T, Unger T. Willing to pay for quality personalization? Trade-off between quality and privacy. Eur J Inf Syst. 2012;21(6):621-642.
12. Lin TC, Wu S, Hsu JSC, Chou YC. The integration of value-based adoption and expectation-confirmation models: An example of IPTV continuance intention. Decis Support Syst. 2012;54(1):63-75.
13. Liu F, Zhao X, Chau PY, Tang Q. Roles of perceived value and individual differences in the acceptance of mobile coupon applications. Internet Res. 2015;25(3):471-495.
14. Maher CA, Davis CR, Curtis RG, Short CE, Murphy KJ. A physical activity and diet program delivered by artificially intelligent virtual health coach: Proof-of-concept study. JMIR mHealth uHealth. 2020;8(7):e17558.
15. Majumder S, Deen MJ. Smartphone sensors for health monitoring and diagnosis. Sensors. 2019;19(9):2164.
16. Moon JW, Kim YG. Extending the TAM for a World-Wide-Web context. Inf Manage. 2001;38(4):217-230.
17. Niyomyart A, Ruksakulpiwat S, Benjasirisan C, Phianhasin L, Nigussie K, Thorngthip S, *et al*. Current status of barriers to mHealth access among patients with stroke and steps toward the digital health era: Systematic review. JMIR mHealth uHealth. 2024;12:e54511.
18. Schomakers EM, Lidynia C, Vervier LS, Calero Valdez A, Ziefle M. Applying an extended UTAUT2 model to explain user acceptance of lifestyle and therapy mobile health apps: Survey study. JMIR mHealth uHealth. 2022;10(1):e27095.
19. Shen Y, Sa HJ, Han JH. Continued use of artificial intelligence coaching services: Application of the value-based acceptance model. Soc Behav Personal. 2024;52(9):1-15.
20. Singh S, Singh N, Kalinić Z, Liébana-Cabanillas FJ. Assessing determinants influencing continued use of live streaming services: An extended perceived value theory of streaming addiction. Expert Syst Appl. 2021;168:114241.
21. Sirdeshmukh D, Singh J, Sabol B. Consumer trust, value, and loyalty in relational exchanges. J Mark. 2002;66(1):15-37.
22. Swait J, Sweeney JC. Perceived value and its impact on choice behavior in a retail setting. J Retail Consum Serv. 2000;7(2):77-88.
23. Tropea P, Schlieter H, Sterpi I, Judica E, Gand K, Caprino M, *et al*. Rehabilitation, the great absentee of virtual coaching in medical care: Scoping review. J Med Internet Res. 2019;21(10):e12805.
24. Van der Merwe H, Terblanche N. Individual propensity to use an AI coaching chatbot in the contact centre environment. J Work-Appl Manage. 2025. [Epub ahead of print].
25. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Q. 2003;27(3):425-478.
26. Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Q. 2012;36(1):157-178.
27. Wachholz F, Manno S, Schlachter D, Gamper N, Schnitzer M. Acceptance and trust in AI-generated exercise plans among recreational athletes and quality evaluation by experienced coaches: A pilot study. BMC Res Notes. 2025;18(1):12.
28. Wang H, Tao D, Yu N, Qu X. Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. Int J Med Inform. 2020;139:104156.
29. Wang Y, Gu J, Wang S, Wang J. Understanding consumers' willingness to use ride-sharing services: The roles of perceived value and perceived risk. Transp Res Part C Emerg Technol. 2019;105:504-519.
30. Weimann TG, Schlieter H, Brendel AB. Virtual coaches: Background, theories, and future research directions. Bus Inf Syst Eng. 2022;64(4):515-528.
31. Wu T, Jiang N, Sharif SP, Chen M. Explaining subscription intention for video streaming platforms in China: Integrating the UTAUT2 model, perceived value theory, and SOR theory. PLoS One. 2025;20(5):e0322860.
32. Yang H, Yu J, Zo H, Choi M. User acceptance of wearable devices: An extended perspective of perceived value. Telemat Inform. 2016;33(2):256-269.