Social Behavior and Personality
an international journal

Social Behavior and Personality, Volume 52, Issue 9, e13493
https://doi.org/10.2224/sbp.13493
www.sbp-journal.com

Continued use of artificial intelligence coaching services: Application of the value-based acceptance model

YaWen Shen[1], Hye Ji Sa[2], Jee-Hoon Han[3]

[1]Sports Department, Zhongyuan University of Technology, People's Republic of China
[2]Sport Memory Culture Institute, Woosuk University, Republic of Korea
[3]Department of Sport Industry Studies, Yonsei University, Republic of Korea

How to cite: Shen, Y., Sa, H. J., & Han, J.-H. (2024). Continued use of artificial intelligence coaching services: Application of the value-based acceptance model. *Social Behavior and Personality: An international journal, 52*(9), e13493

We used the value-based acceptance model to examine what drives continued usage of artificial intelligence coaching services. Analyzing survey data from 320 users in South Korea who had engaged in sports activities facilitated by artificial intelligence coaching services, our structural equation modeling results showed that usefulness and enjoyment positively predicted users' perceived value of the services, positively influencing their continued usage intention. Conversely, cost negatively predicted perceived value and complexity did not significantly affect perceived value. Thus, we can conclude that emphasizing benefits and minimizing costs are crucial for enhancing perceived value. Service providers should develop strategies to increase this value to maintain user engagement.

Keywords
artificial intelligence coaching service, sports coaching, perceived value, continued usage intention

Article Highlights

- Usefulness and enjoyment were found to positively predict the perceived value of artificial intelligence coaching services.
- Cost negatively predicted the perceived value of these services, whereas complexity did not have a significant influence on perceived value.
- We observed a significant relationship between perceived value and the intention to continue using artificial intelligence coaching services.
- Service providers should develop strategies to increase perceived value, focusing on the aspects of usefulness and enjoyment, and addressing cost concerns.

Recent technological advancements in artificial intelligence (AI) have profoundly impacted various industry sectors, including the realm of sports. The extended duration of the COVID-19 pandemic has precipitated a surge in the adoption of non-face-to-face services within leisure sports, a development significantly influenced by AI technologies (Han & Park, 2021). These technologies have been pivotal in the postpandemic era, fostering new business models by leveraging personal health data to deliver customized feedback, thereby transforming the landscape of sports participation (Lattie et al., 2019; Thompson, 2022; J. Wang et al., 2019).

In particular, the emergence of AI coaching technologies marks a notable paradigm shift in the enhancement of personal training and athletic skill development within the sports domain. These innovative services, utilizing data

CORRESPONDENCE Hye Ji Sa, Sport Memory Culture Institute, Woosuk University, 443, Samnye-ro, Samney-eup, Wanju-gun, Jeollabuk-do, Republic of Korea 55338. Email: hyeji40@gmail.com

metrics such as exercise volume and heart rate, facilitate the creation of individualized training regimens. This approach not only enhances the efficiency and safety of training but also augments participant engagement; by analyzing physical movements, these AI coaching systems are adept at identifying and rectifying incorrect postures and exercise habits (Yu et al., 2019). Furthermore, the incorporation of voice feedback within these services—providing motivation, commendation, and essential information—has been shown to have a significant positive influence on users' health behaviors, thereby contributing to the overall training experience (Graßmann & Schermuly, 2021; Y. Lee & Lim, 2015; Terblanche et al., 2023).

The assessment of user acceptance and the intention to utilize technology plays an integral role in determining the success of technological applications (Y. Kim et al., 2017). Scholarly research in this domain, notably through frameworks like the technology acceptance model (TAM; Davis, 1989) and the unified theory of acceptance and use of technology (Venkatesh et al., 2003), has predominantly concentrated on evaluating the advantageous attributes of technology, such as its perceived usefulness and ease of use. However, the value-based adoption model (VAM; H.-W. Kim et al., 2007), which draws upon Zeithaml's (1988) seminal concept of perceived value, offers a more holistic perspective by integrating both the advantageous and sacrificial elements inherent in the technology-adoption process (H.-W. Kim et al., 2007; S. Y. Lee et al., 2019). This dualistic approach, which gives equal consideration to the benefits and costs associated with technology use, has been empirically demonstrated to exert a significant influence on consumers' propensity to continue using a technology (Kwon & Son, 2021; Lin et al., 2012; Zeithaml, 1988).

In this scholarly inquiry we delved into the ramifications of AI coaching services as regards participation in leisure sports in the context of the postpandemic landscape, with a specific focus on remote and digital modalities. Our objective was to elucidate user perceptions and ascertain the determinants that drive the adoption of AI coaching services, utilizing the theoretical framework of the VAM. We methodically assessed the perceived advantages, such as utility and enjoyment, alongside the perceived drawbacks, including financial outlay and complexity, and analyzed how these factors collectively and individually predict users' continued engagement with these services. *Artificial intelligence coaching* within the realm of leisure sports is characterized as technologically advanced systems that furnish customized coaching and training experiences through applications, online platforms, and virtual reality environments, which are tailored to individual athletic performance metrics and personal objectives. This research will be instrumental in enhancing comprehension of the role of AI coaching in leisure sports and in guiding future innovations and developments within this sector.

Artificial Intelligence Coaching Services

We explored the role of AI coaching services in influencing health behavior changes, focusing in particular on their use in leisure sports contexts. According to Prochaska and Velicer (1997), the process of health behavior change is characterized by a sequence of stages: precontemplation, contemplation, preparation, action, and maintenance. The critical transition from the action to the maintenance stage is pivotal for the enduring success of health behavior modifications, and is typically achieved through social reinforcement provided by mediators (Sundel & Sundel, 2018; Watson & Tharp, 2013). These mediators may encompass social entities that offer either positive reinforcement or corrective feedback.

In the realm of non-face-to-face services, AI coaching services, functioning as surrogate voice feedback coaches, have the potential to emulate social mediators. They dispense not only motivational support and emotional sustenance but also health-related information (Y. Lee & Lim, 2015). We delved into the specific modalities through which AI coaching services influence user engagement and sustained involvement in sports activities, focusing in particular on the capacity of these services to approximate social interaction, a key element in the maintenance of health behavior change.

The Value-Based Adoption Model

The VAM was originally proposed by H.-W. Kim et al. (2007) to explain consumers' intention to adopt mobile commerce. The researchers argued that existing models like the TAM did not fully capture the factors influencing the adoption of new information and communication technologies. Prior research into technology adoption and usage intentions (Choi & Lee, 2019; C. Luo, 2014; Y. Wang et al., 2004; Yu et al., 2019; Zeithaml, 1988) integrated the VAM's proposed constructs of perceived benefits and perceived sacrifices, examining their effects on perceived value and the intention to adopt technology. *Perceived benefit* is the evaluation made by consumers about the superiority and excellence they recognize while using a specific product or service, which then becomes an attitude toward the product or service (Zeithaml, 1988). In examining technology adoption, the VAM stands out by delving into user acceptance nuances. Unlike the TAM and the unified theory of acceptance and use of technology, which focus on facilitators of technology use, the VAM evaluates the net worth of technology from the user's viewpoint (Pal et al., 2020). It stresses the balance of perceived benefits against perceived sacrifices, offering a dualistic perspective that acknowledges both the advantages and costs associated with technology adoption. The VAM's consumer-centric angle highlights the subjective nature of value perception, positing it as a crucial factor for adoption intention (Erdmann et al., 2023). This holistic approach makes the VAM particularly relevant where the costs of technology adoption are as significant as the benefits in influencing user decisions.

In line with these studies, perceived benefits, which are typically linked to the usefulness and enjoyment of the technology (Davis, 1989; Venkatesh & Davis, 2000), and perceived sacrifices, which are associated with the costs and complexity of using the technology (H.-W. Kim et al., 2007), have been investigated for their impact on technology acceptance. This study extended this investigation to the domain of AI coaching services, hypothesizing structural relationships among the VAM variables to comprehend users' continued usage intention. The research model depicted in Figure 1 is based on the interrelations of these concepts as evidenced in the existing literature.

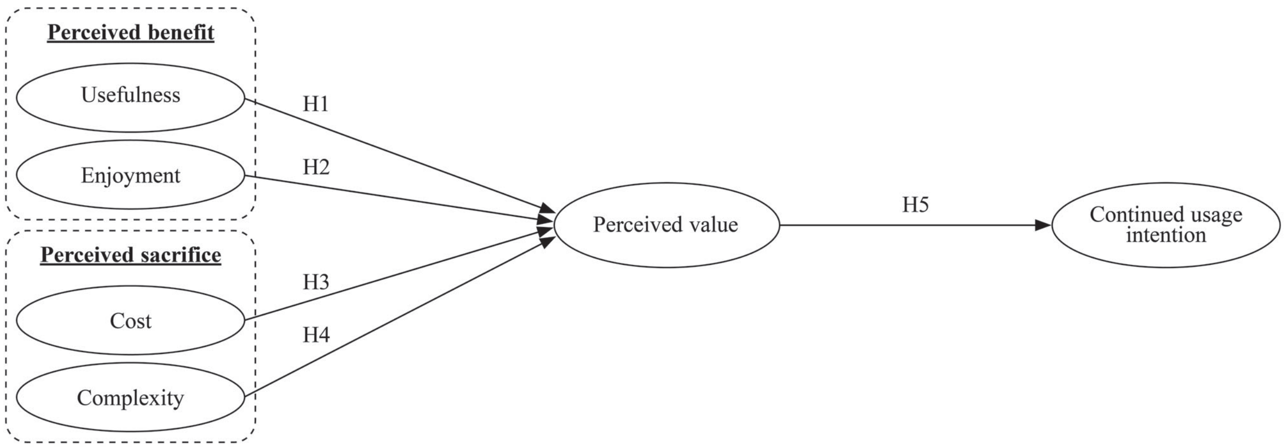

Figure 1. *Research Model*

Relationship Between Perceived Benefits of Technology Use and Perceived Value

Usefulness of information technology refers to the degree of belief in performance obtained through the use of this technology (Seo & Kim, 2020). It is a measure of extrinsic motivation and can be used to explain the outcomes of technology acceptance, with users who perceive high (vs. low) usefulness considering the use of technology as a more meaningful act (S. Lee, 2021; Venkatesh et al., 2003). Looking at previous research on the dimensions of perceived benefit, Davis (1989) defined usefulness as the belief that using a new system or technology will enhance one's job performance, leading to improved achievements or work outcomes. People who feel that a new technology is useful perceive its use as more beneficial than not using it, which represents the total value perceived in the process of using the new technology, and individuals make choices about the evaluation of technology acceptance outcomes and technology acceptance behavior through the perception of usefulness (Venkatesh, 1999).

In adopting information technology, intrinsic motivations (e.g., enjoyment) and extrinsic motivations (e.g., usefulness) play a crucial role (Ahn et al., 2007; K. S. Lee & Lee, 2011). *Enjoyment* is measured by the positive or negative responses people experience in an environment (Eroglu et al., 2003), and it refers to the degree to which the process of using a product or service is pleasurable, regardless of the outcomes of the usage behavior (Malone, 1981). The *hedonic benefit*, or pleasure, is the utility derived from the emotional state or feelings formed by the product; when consumers experience or perceive enjoyment from using technology, they are more likely to accept it (Oh, 2017).

According to Davis (1989), the enjoyment perceived in the process of using technology encourages more diverse use of that technology, indicating that the emotion of enjoyment can positively transform the perceived value of adopting new technology. Thus, we formed the following hypotheses:
Hypothesis 1: Usefulness will positively predict perceived value.
Hypothesis 2: Enjoyment will positively predict perceived value.

Relationship Between Perceived Sacrifices Associated with Technology Use and Perceived Value

Perceived sacrifice refers to the monetary and nonmonetary costs that customers incur when purchasing a product or service (Zeithaml, 1988). This can be explained by the complexity related to the costs that must be paid or given up when using a product or service. The monetary element, or *perceived cost*, signifies the actual financial amount associated with the use of new technology (Biswas et al., 2006). The cost perceived by users is based on their perception of the actual selling price of the product, service, or technology. Users unfamiliar with new technology may find it difficult to assess costs and, therefore, estimate expenses based on similar past experiences (Grewal et al., 1998). Consequently, the cost-related risk increases due to uncertainty about the product, requiring consumers to estimate and pay costs without direct experience (Biswas et al., 2006). I. Lee and Lee (2015) and H.-Y. Wang and Wang (2010) found that perceived costs negatively influence perceived value. Monetary sacrifices are typically understood as direct costs incurred, while time and effort represent nonmonetary sacrifices that also impact the perceived value of a service (Cronin et al., 2000; H.-W. Kim et al., 2007).

Complexity refers to the effort needed by consumers to effectively use the functions of a product (Alba & Hutchinson, 1987). It denotes the degree of difficulty perceived in the use of a service or product and is closely related to acceptance of the service. Greater complexity requires more time and effort from consumers to adopt the technology. Thus, the more easily a new technology is understood and used by the user, the faster the product or service will be accepted. Conversely, greater complexity can lead to dissatisfaction with the new product or service (Rogers et al., 2008). K. T. Kim and Song (2020) found that higher complexity significantly reduces perceived value and the intention to use AI-based mobile applications. Y. Kim et al. (2021) also found in their study with AI platform users that complexity negatively affects perceived value. Thus, we established the following hypothesis:
Hypothesis 3: Cost will negatively predict perceived value.
Hypothesis 4: Complexity will negatively predict perceived value.

Relationship Between Perceived Value and Continued Usage Intention

Value is judged based on the benefits or profits that individuals anticipate from a product or service, playing a pivotal role in consumption decisions and influencing consumer behavior (Yi & La, 2003). Bolton and Drew (1991) and Sirdeshmukh et al. (2002) noted that a positive perception of a product or service's value can increase the intention to repurchase, while a negative perception can decrease this intention. Therefore, consumers are more likely to continue using a product or service when they perceive its value to be high. This concept is supported by several studies within the framework of the VAM. Thus, we formed the following hypothesis:
Hypothesis 5: Perceived value will positively predict the intention to continue using artificial intelligence coaching services.

Method

Participants and Procedure

We examined general participants involved in leisure sports, who were not necessarily athletes but who had engaged in sports activities facilitated by AI coaching services. In collecting data, we targeted individuals with experience in using AI coaching services for sports activities that utilize motion sensing to enhance interaction and engagement. Participants were required to have taken part in at least one session lasting a minimum of 30 minutes. The study focused on the most-utilized sports in South Korea for AI coaching services—specifically, fitness and golf—where motion sensing plays a critical role in providing real-time feedback and personalized coaching. Data collection was facilitated through an online survey distributed by a survey company during August 5–10, 2023. The survey reached potential participants in the company's database via email, resulting in 320 valid responses. All participants resided in South Korea. Prior to the survey, informed consent was secured from every participant and they were thoroughly briefed about the survey's nature and objectives. Detailed demographic and general characteristics of the participants can be found in Table 1.

Table 1. *Characteristics of the Participants*

Characteristics		*n*	Ratio (%)
Gender	Male	116	36.3
	Female	204	63.7
Age (years)	20s	84	26.3
	30s	136	42.5
	40s	48	15.0
	50s	36	11.3
	60s or over	16	5.0
Frequency of artificial intelligence coaching experience	1–2	144	45.0
	3–5	84	26.3
	6–10	34	10.6
	11–15	14	4.4
	16–20	4	1.3
	20+	40	12.5
Reason for usage of artificial intelligence coaching	Weight loss	72	22.5
	Muscle mass and health improvement	86	26.9
	Posture correction	76	23.8
	Cost and time saving	86	26.9
Method of learning about artificial intelligence coaching	Internet search	204	63.7
	Social media advertising	76	23.8
	Word of mouth	40	12.5
Total		320	100

Measures

We adapted our questionnaire from items utilized by H.-W. Kim et al. (2007) and H.-Y. Wang and Wang (2010). Variables measured comprised perceived benefits (usefulness and enjoyment), perceived sacrifices (cost and complexity), perceived value, and continued usage intention, encompassing 24 items across these categories. Modifications and additions were made to these items to align them with the specific context of this study. A 5-point Likert response scale (1 = *never*, 5 = *always*) was used for all measures. Additionally, to understand the demographic profiles of participants, we asked them to provide their gender, age, number of service experiences, primary considerations in using AI services, main purpose(s) for using these services, and method of discovery of these services.

Factor Analysis and Reliability Testing

We established the validity of the measurement instrument through a rigorous validation process encompassing content validity, construct validity, and model fit assessments. Content validity was initially ascertained through evaluation by an academic peer. Subsequently, we conducted a confirmatory factor analysis to assess construct validity and model fit. As shown in Table 2, the confirmatory factor analysis results satisfied the criteria for a good level of fit to the data according to established criteria (Hu & Bentler, 1999; MacCallum et al., 1996).

Cronbach's alpha values exceeded .70, confirming the measures' reliability (Van de Ven & Ferry, 1980). Convergent validity was further established by calculating the construct reliability and average variance extracted for all factors, with construct reliability values exceeding .60 and average variance extracted surpassing .50 (Bagozzi & Yi, 1988). The detailed analysis results are presented in Table 2.

Table 2. *Results of the Confirmatory Factor and Reliability Analyses*

Factor	Item	Standardized estimate	Error variation	CR	AVE	Cronbach's α
Usefulness	AI coaching services are useful.	.845	.138	.889	.672	.784
	AI coaching services provide me with convenience.	.736	.262			
	Through AI coaching services, I can quickly find out the information I want.	.611	.249			
	I can effectively check the information I want in AI coaching services.	.584	.312			
Enjoyment	Using AI coaching services is enjoyable and fun.	.772	.271	.893	.677	.872
	The content of AI coaching services is interesting and diverse.	.791	.253			
	Using AI coaching services alleviates boredom.	.707	.338			
	AI coaching services enhance the enjoyment of my life.	.803	.263			
Cost	AI coaching services do not provide superior service compared to the financial cost paid.	.878	.226	.890	.676	.840
	Using AI coaching services requires a lot of cost (time, effort).	.892	.178			
	The price for using AI coaching services is unreasonable.	.606	.378			
	The price for using AI coaching services is not cheap.	.662	.352			
Complexity	The process of using AI coaching services is complicated.	.754	.279	.902	.699	.867
	Understanding the detailed features of AI coaching services is difficult.	.744	.312			
	AI coaching services are more complex compared to traditional coaching services.	.837	.226			
	The method of using AI coaching services is generally complex.	.811	.248			
Perceived value	The benefits provided by AI coaching services are valuable.	.663	.248	.906	.709	.814
	AI coaching services are worth the effort required to use them.	.768	.231			
	Overall, AI coaching services have value.	.779	.273			
	I think it is worth using AI coaching services.	.769	.159			
Continued usage intention	I intend to continue using AI coaching services.	.863	.140	.941	.841	.911
	I will make an effort to reuse AI coaching services.	.848	.146			
	I am willing to use AI coaching services again.	.878	.134			
	I will use AI coaching services for as long as possible.	.717	.159			
χ^2 = 731.943, *df* = 307, TLI = .90, CFI = .920, RMSEA = .066						

Note. AI = artificial intelligence; CR = construct reliability; AVE = average variance extracted; TLI = Tucker–Lewis index; CFI = comparative fit index; RMSEA = root-mean-square error of approximation.

Data Processing

This research employed SPSS 24.0 and Amos 22.0 for data analysis. We began with a frequency analysis to delineate the general characteristics of the data, followed by a confirmatory factor analysis to establish the reliability and validity of the survey tool. The internal consistency of the questionnaire was assessed using Cronbach's alpha. Subsequently, we conducted a correlation analysis to examine the interrelationships among variables such as usefulness, enjoyment, complexity, cost, perceived value, and the intention to continue the use of AI coaching services in sports. Last, we tested the research hypotheses through path analysis using structural equation modeling.

Results

Correlation Analysis of Factors

The correlation analysis results detailed in Table 3 show that the Pearson product-moment correlation coefficients between the latent variables were significant and did not exceed .80.

Table 3. *Correlation Analysis Results*

	M	*SD*	1	2	3	4	5	6
1. Usefulness	3.95	0.54	—					
2. Enjoyment	3.70	0.71	.598**	—				
3. Cost	3.49	0.78	−.097*	−.094*	—			
4. Complexity	3.01	0.71	−.152**	−.104*	.415**	—		
5. Perceived value	3.57	0.56	.529**	.620**	−.328*	−.053*	—	
6. Continued usage intention	3.51	0.73	.526**	.664**	−.056*	−.021*	.772**	—

Note. * $p < .05$. ** $p < .01$.

Model Fit

The structural model of this study was analyzed using maximum likelihood estimation for the model's parameters. The model fit the data well, $\chi^2 = 731.943$, $df = 307$, CFI = .90 (> .90), TLI = .91 (> .90), RMSEA = .080 (< .10).

Hypothesis Testing

Our results revealed the importance of perceived value in influencing continued usage intention for AI coaching services. Hypothesis 1, which suggested that the perceived usefulness of AI coaching services would positively predict perceived value, was supported by our findings. Hypothesis 2, asserting that enjoyment would similarly predict perceived value, was also supported. Hypothesis 3, which anticipated a negative impact of cost on perceived value, was supported. Hypothesis 4, which predicted a negative relationship between complexity and perceived value, was not supported by our data. On the other hand, Hypothesis 5 was strongly supported, revealing that perceived value greatly influenced the intention to continue using AI coaching services.

The detailed statistical evidence for these findings is presented in Table 4 and Figure 2. The results highlight the critical role that both positive aspects, such as usefulness and enjoyment, and negative aspects, like cost, appeared to play in shaping users' perceived value of AI coaching services. Despite the lack of significant contribution from complexity, the overall pattern suggests the pivotal influence of perceived value in participants' continued usage intention, offering actionable insights for service providers aiming to bolster user engagement in leisure sports through AI coaching.

Table 4. *Path Analysis Results*

Hypothesis	Path	Path coefficient	*SE*	*t*	Hypothesis supported (Y/N)
H1	Usefulness → Perceived value	.320	0.064	4.982***	Y
H2	Enjoyment → Perceived value	.429	0.047	9.122***	Y
H3	Cost → Perceived value	−.194	0.039	−3.239*	Y
H4	Complexity → Perceived value	.007	0.032	0.221	N
H5	Perceived value → Continued usage intention	.760	0.109	11.563***	Y

Note. * $p < .05$. *** $p < .001$.

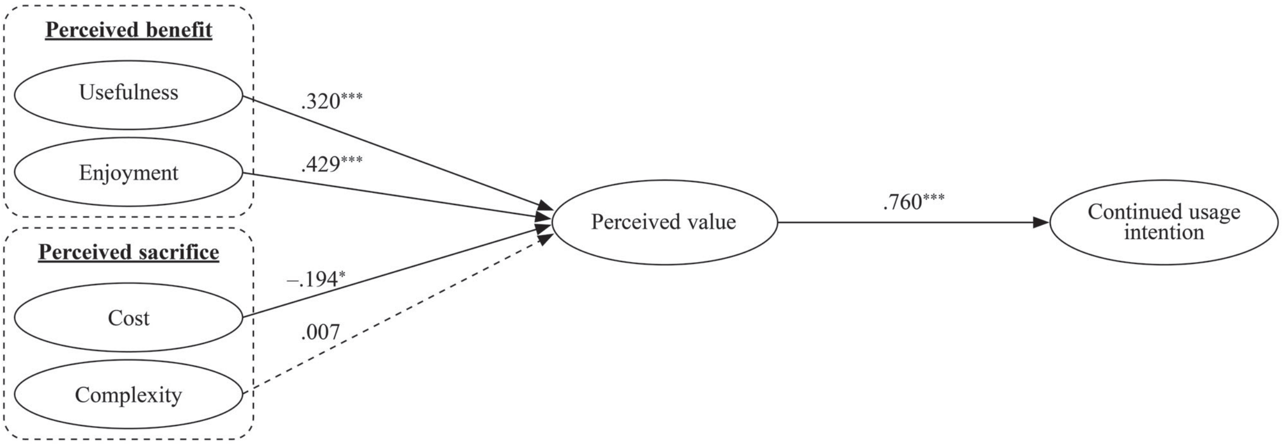

Figure 2. *Path Analysis Results*
Note. Solid lines denote significant relationships. The dashed line denotes nonsignificance.

Discussion

This study analyzed the intention to continue using AI coaching services among sports participants. The results indicate that perceived benefits, namely usefulness and enjoyment, had a positive and significant impact on the perceived value of these services. Perceived sacrifice, in the form of cost, had a significant negative impact on perceived value, whereas complexity did not have a significant impact. Finally, perceived value significantly influenced continued usage intention.

The Impact of Perceived Benefits on Perceived Value

The usefulness and enjoyment of AI sports coaching services were found to predict perceived value, supporting Hypotheses 1 and 2. Prior research has suggested that when users experience more enjoyment using information technology systems, their motivation to interact with these systems is enhanced (M. M. Luo & Remus, 2014). Therefore, related technological services should be designed to provide users with enjoyable experiences, interesting learning methods, and attractive technology (Balog & Pribeanu, 2010). Han and Park (2021) emphasized that AI services provide both useful aspects, such as motion analysis and feedback, and enjoyable experiences. Further, H.-W. Kim et al. (2007) observed significant effects of the usefulness and enjoyment of mobile internet use on perceived value. Additionally, the benefits obtainable from predicting e-learning service consumers' perceived value based on the positive impacts of usefulness and enjoyment allow providers to maximize customers' perceived value (Liao et al., 2022). Liao et al. (2022) explained that in e-learning contexts, usefulness has a greater impact on perceived value than does enjoyment; thus, offering rich learning content and focusing on learners' experiences can increase perceived value. The greater the perceived benefits, the more likely consumers are to evaluate a product or service positively, which can, in turn, increase perceived value.

The Impact of Perceived Sacrifices on Perceived Value

We found that the perceived sacrifice of cost negatively predicted the perceived value of AI coaching services for sports participants, supporting Hypothesis 3. However, complexity was not a significant predictor of perceived value, so Hypothesis 4 was not supported.

Users are more likely to adopt technology when the benefits it provides justify the cost. Here, cost includes not only monetary expenses but also factors such as time, effort, and the learning curve. Users evaluate the costs associated with adopting and using technology in comparison to potential benefits, and such comparisons play a crucial role in determining the adoption of technology. Our result that cost negatively predicts perceived value is consistent with the findings of numerous previous studies. For instance, H.-Y. Wang and Wang (2010), in their research on the intention to use mobile hotel reservation apps, found that the subfactor of perceived cost, which is a component of sacrifice, negatively affected perceived value. Similarly, C. Luo (2014) studied the intention to use mobile commerce services and found that perceived cost and perceived effort negatively influenced users' perceived value. Furthermore, Li et al. (2022) examined the predictors of consumer behavior in online-to-offline services and found that perceived cost significantly influenced perceived value, supporting the results of this study.

On the other hand, our result that complexity did not significant predict perceived value differs from the findings of previous studies (Jeong & Kim, 2022; Y. Kim et al., 2017). According to J.-H. Lee and Kim (2021), even when technology is perceived as complex, this does not significantly affect perceived value. They explained that this phenomenon is due to the continuous development of information and communication technology, leading to greater familiarity and proficiency among consumers. In other words, even if consumers perceive a new technology as highly complex, familiarity and proficiency gained from their use of previous versions of related technologies can help overcome this barrier. Initially, consumers may find a new technology or service challenging, but this challenge may not be a significant factor in evaluating the overall value of the service. The aforementioned studies suggested, in particular, that complexity may not serve as a decisive criterion for assessing value, especially when users have the opportunity to gain familiarity and proficiency over time. Moreover, our study highlights that the demographic characteristics of the participants, especially the age group of individuals in their 20s and 30s, have a notable influence on the perceived value of AI coaching services. This influence appears to be consistent across different levels of service complexity, which suggests that younger users may place a different level of importance on certain attributes of AI coaching services, which, in turn, affects their overall valuation of the service. This implies that users' perceived sacrifices, as identified in various studies, act as critical barriers to information technology adoption (Cho & Jeon, 2020; H.-W. Kim et al., 2007; C. Luo, 2014).

Impact of Perceived Value of Continued Usage Intention

We found that the perceived value of AI coaching services significantly predicted continued usage intention, supporting Hypothesis 5. The core concept of the VAM is that consumers' behavioral intentions are primarily determined by the relative value they perceive in benefits and losses (H.-W. Kim et al., 2007). Perceived value has long been emphasized as a crucial factor in consumer behavior research that determines actual consumption behavior. This study supports the importance of perceived value in the acceptance of new technology and services, aligning with numerous previous studies (Roostika, 2012; Shelvia et al., 2020).

Perceived value represents how consumers evaluate and perceive the inherent characteristics of a product or service. J. Kim (2020) and Woodruff (1997) suggested that consumers consider perceived value when deciding to purchase or use a product or service, a viewpoint similar to that of Sweeney and Soutar (2001). Accordingly, when consumers assign high value to a new technology or service it can be expected that they will have a higher continued usage intention. This perspective has been empirically supported in various studies related to the intention to use new technology or services. For example, Roostika (2012) found that consumers who perceive high value in new mobile internet information and communications technology are more likely to form positive intentions to use it. Mathavan et al. (2024) conducted research on the acceptance of fitness wearable products and found that perceived value significantly influences usage intention.

These research findings emphasize the significant role of perceived value in the successful market entry of products or services and increasing consumer acceptance. In the case of AI coaching services, the additional cost associated with the need for sensors or hardware, unlike traditional video games or home training programs, can be a barrier to users' continuous use. However, the findings of this study suggest that if consumers have a high evaluation of the value of AI coaching services, their continued usage intention can be strengthened. This underscores the need for consideration of how to effectively communicate the value of AI coaching services to consumers and persuade them to continue using the service.

Practical Implications

This study provides an in-depth examination of AI coaching services utilized by leisure sports participants, accentuating the positive perceptions of the utility of these services and the enjoyment they offer. Our findings underscore the importance of developing strategies that highlight service benefits to enhance users' adoption and engagement. We recommend the use of promotional strategies, particularly those involving immersive wearable devices and interactive virtual games, to amplify utility and enjoyment perceptions.

The research delineates that perceived costs (sacrifices) negatively predict the perceived value of AI coaching services, whereas the complexity of these services does not significantly alter this perception. These findings fill gaps in the existing literature by incorporating emotional responses, costs, and sacrifices into the evaluation of technological utility through the lens of the VAM.

From a health psychology perspective, the implications of these findings are significant. In light of the escalating global health challenges, such as the rise of chronic diseases, there is a pressing need to embed technology in health promotion (Kaplan & Stone, 2013). AI coaching services, through their simulation of personal coaching experiences, show promise in increasing physical activity engagement, thereby aiding in the overarching objective of enhancing public health.

The significance of our study extends to the assimilation of innovative technology into day-to-day life, with the younger population displaying a particular inclination toward using these services (Olson et al., 2011). This suggests that the future of AI coaching may be closely aligned with meeting the expectations and lifestyles of this demographic.

Moreover, we found that perceived value is a predominant factor influencing the intention to use AI coaching services. Bolstering this perceived value has the potential to grow service usage and expand participation in leisure sports. Thus, we advocate for a focus on amplifying benefits and minimizing sacrifices to encourage sustained use of these services. Overall, the study provides valuable insights into how leisure sports participants weigh the advantages against the sacrificial aspects when deciding whether to use AI services.

Limitations and Future Research Directions

This study has certain limitations. Specifically, the intensity and duration of engagement with AI coaching services can differ significantly between individuals, even within the same experience, which has implications for their intention to continue using such services. Given these differences, future research could explore broader cognitive value factors and generational variations in value perception and continued usage intention. We also recommend considering regional differences in internet environments and device adoption in future research, as these factors could lead to different outcomes in other areas. By examining these diverse aspects, future studies can provide a more nuanced understanding of AI service adoption in leisure sports and will contribute to the development of more effective health-promotion interventions.

References

Ahn, T., Ryu, S., & Han, I. (2007). The impact of web quality and playfulness on user acceptance of online retailing. *Information and Management*, *44*(3), 263–275.
https://doi.org/10.1016/j.im.2006.12.008

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of Consumer Research*, *13*(4), 411–454.
https://doi.org/10.1086/209080

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*, 74–94.
https://doi.org/10.1007/BF02723327

Balog, A., & Pribeanu, C. (2010). The role of perceived enjoyment in the students' acceptance of an augmented reality teaching platform: A structural equation modelling approach. *Studies in Informatics and Control*, *19*(3), 319–330.
https://doi.org/10.24846/v19i3y201011

Biswas, D., Biswas, A., & Das, N. (2006). The differential effects of celebrity and expert endorsements on consumer risk perceptions. The role of consumer knowledge, perceived congruency, and product technology orientation. *Journal of Advertising*, *35*(2), 17–31.
https://doi.org/10.1080/00913367.2006.10639231

Bolton, R. N., & Drew, J. H. (1991). A multistage model of customers' assessments of service quality and value. *Journal of Consumer Research*, *17*(4), 375–384.
https://doi.org/10.1086/208564

Cho, W.-H., & Jeon, H.-M. (2020). Consumers' acceptance intention on introduction to technology-based self-service (TBSS) in fast food restaurants: Focusing on the value-based acceptance model [In Korean]. *Foodservice Management Society of Korea*, *23*(6), 105–129.
https://doi.org/10.47584/jfm.2020.23.6.105

Choi, K. O., & Lee, H. R. (2019). A study on the relationships among flight search mobile application users' perceived benefit, perceived sacrifice, perceived value and continuous use intentions by using the value-based adoption model [In Korean]. *Journal of Tourism Sciences*, *43*(8), 115–135.

Cronin, J. J., Jr., Brady, M. K., & Hult, G. T. M. (2000). Assessing the effects of quality, value, and customer satisfaction on consumer behavioral intentions in service environments. *Journal of Retailing*, *76*(2), 193–218.
https://doi.org/10.1016/S0022-4359(00)00028-2

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.
https://doi.org/10.2307/249008

Erdmann, A., Mas, J. M., & Arilla, R. (2023). Value-based adoption of augmented reality: A study on the influence on online purchase intention in retail. *Journal of Consumer Behaviour*, *22*(4), 912–932.
https://doi.org/10.1002/cb.1993

Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2003). Empirical testing of a model of online store atmospherics and shopper responses. *Psychology and Marketing*, *20*(2), 139–150.
https://doi.org/10.1002/mar.10064

Graßmann, C., & Schermuly, C. C. (2021). Coaching with artificial intelligence: Concepts and capabilities. *Human Resource Development Review*, *20*(1), 106–126.
https://doi.org/10.1177/1534484320982891

Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The effects of price-comparison advertising on buyers' perceptions of acquisition value, transaction value, and behavioral intentions. *Journal of Marketing*, *62*(2), 46–59. https://doi.org/10.1177/002224299806200204

Han, J. S., & Park, S. B. (2021). Hyperconnectivity between artificial intelligence and elementary physical education in the era of the 4th industrial revolution [In Korean]. *Korean Journal of Elementary Education*, *31*, 159–172.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jeong, J., & Kim, G. (2022). The effects of metaverse characteristics and value recognition on service adoption intention [In Korean]. *Journal of Korea Parliamentary Law Institute*, *15*(1), 99–115. https://doi.org/10.56352/SMJ.2022.15.1.07

Kaplan, R. M., & Stone, A. A. (2013). Bringing the laboratory and clinic to the community: Mobile technologies for health promotion and disease prevention. *Annual Review of Psychology*, *64*, 471–498. https://doi.org/10.1146/annurev-psych-113011-143736

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, J. (2020). Perceived value and adoption intentions of the mobile apps in online travel agency based on the value-based adoption model [In Korean]. *International Journal of Tourism Management and Sciences*, *35*(5), 25–49. https://doi.org/10.21719/IJTMS.35.5.2

Kim, K. T., & Song, J. S. (2020). A study of factors affecting consumers' intention to use artificial intelligence-based mobile user interface design – Based on the value-based adoption model [In Korean]. *Journal of the Korean Society Design Culture*, *26*(2), 7–27. https://doi.org/10.18208/ksdc.2020.26.2.7

Kim, Y., Kim, J.-Y., Jeong, W., & Shin, Y. (2021). A study on the effect of perceived value and innovation resistance factors on adoption intention of artificial intelligence platform: Focused on drug discovery fields [In Korean]. *KIPS Transactions on Computer and Communication Systems, 10*(12), 329–342. https://doi.org/10.3745/KTSDE.2021.10.12.329

Kim, Y., Park, Y., & Choi, J. (2017). A study on the adoption of IoT smart home service: Using value-based adoption model. *Total Quality Management & Business Excellence, 28*(9–10), 1149–1165. https://doi.org/10.1080/14783363.2017.1310708

Kwon, S., & Son, J. Y. (2021). Factors affecting the viewing intention for untact performance using value-based acceptance model. *Journal of Region & Culture*, *8*(2), 49–68. https://doi.org/10.26654/iagc.2021.8.2.049

Lattie, E. G., Adkins, E. C., Winquist, N., Stiles-Shields, C., Wafford, Q. E., & Graham, A. K. (2019). Digital mental health interventions for depression, anxiety, and enhancement of psychological well-being among college students: Systematic review. *Journal of Medical Internet Research*, *21*(7), Article e12869. https://doi.org/10.2196/12869

Lee, I., & Lee, K. (2015). The internet of things (IoT): Applications, investments, and challenges for enterprises. *Business Horizons*, *58*(4), 431–440. https://doi.org/10.1016/j.bushor.2015.03.008

Lee, J.-H., & Kim, N.-J. (2021). Structural effects of perceived benefits and perceived sacrifice on intention to use a virtual reality tourism experience: Application of the value-based adoption model [In Korean]. *Journal of Tourism and Leisure Research*, *33*(10), 107–122. https://doi.org/10.31336/JTLR.2021.10.33.10.107

Lee, K. S., & Lee, H. R. (2011). The influence of travelers' perception of smart phone services on their attitude and intention to use: An application of TAM and PDA theory [In Korean]. *Journal of Tourism Sciences*, *35*(2), 271–292.

Lee, S. (2021). A study on the influence on the loyalty intention of O2O delivery app service users: From the integrated perspective of technology acceptance, value based, and service quality models [In Korean]. *Korea Management Engineers Society, 26*(1), 99–119.

Lee, S. Y., Yim, H. R., & Kim, H. S. (2019). A study on the relationships among membership users' perceived benefit, sacrifice, value, and continuous use intention by using the value-based adoption model: Focusing on people in their 20s who use CJ Company's membership service [In Korean]. *Culinary Science & Hospitality Research*, *25*(6), 12–22.

Lee, Y., & Lim, Y.-K. (2015). Understanding the roles and influences of mediators from multiple social channels for health behavior change. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing*, *2015*, 1070–1079.
https://doi.org/10.1145/2675133.2685032

Li, H.-M., Han, J.-W., & Lee, I.-Y. (2022). Predicting consumption behavior of sport O2O service in Korea and China: Applying the value-based adoption model [In Korean]. *The Korean Journal of Physical Education*, *61*(6), 1–17.
https://doi.org/10.23949/kjpe.2022.9.61.6.1

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), Article 815.
https://doi.org/10.3390/su14020815

Lin, T.-C., Wu, S., Hsu, J. S.-C., & Chou, Y.-C. (2012). The integration of value-based adoption and expectation–confirmation models: An example of IPTV continuance intention. *Decision Support Systems*, *54*(1), 63–75.
https://doi.org/10.1016/j.dss.2012.04.004

Luo, C. (2014). Study on mobile commerce customer based on value adoption. *Journal of Applied Sciences*, *14*(9), 901–909.
https://doi.org/10.3923/jas.2014.901.909

Luo, M. M., & Remus, W. (2014). Uses and gratifications and acceptance of web-based information services: An integrated model. *Computers in Human Behavior*, *38*, 281–295.
https://doi.org/10.1016/j.chb.2014.05.042

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*(2), 130–149.
https://doi.org/10.1037/1082-989X.1.2.130

Malone, T. W. (1981). Toward a theory of intrinsically motivating instruction. *Cognitive Science*, *5*(4), 333–369.
https://doi.org/10.1207/s15516709cog0504_2

Mathavan, B., Vafaei-Zadeh, A., Hanifah, H., Ramayah, T., & Kurnia, S. (2024). Understanding the purchase intention of fitness wearables: Using value-based adoption model. *Asia-Pacific Journal of Business Administration*, *16*(1), 101–126.
https://doi.org/10.1108/APJBA-04-2022-0166

Oh, J. C. (2017). An empirical study on use-diffusion of AR technology based on the VAM: The moderating effects of positive TRI [In Korean]. *The e-Business Studies*, *18*(5), 225–244.
https://doi.org/10.20462/TeBS.2017.10.18.5.225

Olson, K. E., O'Brien, M. A., Rogers, W. A., & Charness, N. (2011). Diffusion of technology: Frequency of use for younger and older adults. *Ageing International*, *36*(1), 123–145.
https://doi.org/10.1007/s12126-010-9077-9

Pal, D., Arpnikanondt, C., Funilkul, S., & Chutimaskul, W. (2020). The adoption analysis of voice-based smart IoT products. *IEEE Internet of Things Journal*, *7*(11), 10852–10867.
https://doi.org/10.1109/JIOT.2020.2991791

Prochaska, J. O., & Velicer, W. F. (1997). The transtheoretical model of health behavior change. *American Journal of Health Promotion*, *12*(1), 38–48.
https://doi.org/10.4278/0890-1171-12.1.38

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2008). Diffusion of innovations. In D. W. Stacks & M. B. Salwen (Eds.), *An integrated approach to communication theory and research* (2nd ed., pp. 432–448). Routledge.

Roostika, R. (2012). Mobile internet acceptance among university students: A value-based adoption model. *International Journal of Research in Management & Technology*, *2*(1), 21–28.

Seo, H.-M., & Kim, S.-A. (2020). A study on consumer attitudes toward ICT convergence technology of professional sports team: Focused on the extended technology acceptance model (ETAM). *Journal of Digital Contents Society*, *21*(3), 521–528.
https://doi.org/10.9728/dcs.2020.21.3.521

Shelvia, O., Prayitno, A. T., Kartono, R., & Sundjaja, A. M. (2020). Analysis of factors affecting consumer's continuance intention to use mobile payments with a value-based adoption model (VAM) approach. *Psychology and Education*, *57*(9), 2883–2898.

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

Sundel, M., & Sundel, S. S. (2018). *Behavior change in the human services: Behavioral and cognitive principles and applications* (6th ed.). SAGE Publications.
https://doi.org/10.4135/9781506352671

Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. *Journal of Retailing*, *77*(2), 203–220.
https://doi.org/10.1016/S0022-4359(01)00041-0

Terblanche, N., Molyn, J., Williams, K., & Maritz, J. (2023). Performance matters: Students' perceptions of artificial intelligence coach adoption factors. *Coaching: An International Journal of Theory, Research and Practice*, *16*(1), 100–114.
https://doi.org/10.1080/17521882.2022.2094278

Thompson, W. R. (2022). Worldwide survey of fitness trends for 2022. *ACSM's Health & Fitness Journal*, *26*(1), 11–20.
https://doi.org/10.1249/FIT.0000000000000732

Van de Ven, A. H., & Ferry, D. L. (1980). *Measuring and assessing organizations*. John Wiley & Sons.

Venkatesh, V. (1999). Creation of favorable user perceptions: Exploring the role of intrinsic motivation. *MIS Quarterly*, *23*(2), 239–260.
https://doi.org/10.2307/249753

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.
https://doi.org/10.1287/mnsc.46.2.186.11926

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

Wang, H.-Y., & Wang, S.-H. (2010). Predicting mobile hotel reservation adoption: Insight from a perceived value standpoint. *International Journal of Hospitality Management*, *29*(4), 598–608.
https://doi.org/10.1016/j.ijhm.2009.11.001

Wang, J., Qiu, K., Peng, H., Fu, J., & Zhu, J. (2019). AI coach: Deep human pose estimation and analysis for personalized athletic training assistance. *Proceedings of the 27th ACM International Conference on Multimedia*, *2019,* 374–382.
https://doi.org/10.1145/3343031.3350910

Wang, Y., Lo, H.-P., & Yang, Y. (2004). An integrated framework for service quality, customer value, satisfaction: Evidence from China's telecommunication industry. *Information Systems Frontiers*, *6*(4), 325–340.
https://doi.org/10.1023/B:ISFI.0000046375.72726.67

Watson, D. L., & Tharp, R. G. (2013). *Self-directed behavior: Self-modification for personal adjustment*. Cengage Learning.

Woodruff, R. B. (1997). Customer value: The next source for competitive advantage. *Journal of the Academy of Marketing Science*, *25*(2), 139–153.
https://doi.org/10.1007/BF02894350

Yi, Y., & La, S. (2003). The relative effects of three dimensions of service quality on customer service—A comparative study of existing vs. potential customers [In Korean]. *Korean Marketing Association, 18*(4), 67–97.

Yu, H., Seo, I., & Choi, J. (2019). A study of critical factors affecting adoption of self-customisation service – Focused on value-based adoption model. *Total Quality Management and Business Excellence*, *30*, S98–S113.
https://doi.org/10.1080/14783363.2019.1665822

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

