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# AI-Powered Chatbots in Sports E-Commerce: A Stimulus-Organism-Response Perspective on Consumer Behavior

**Halil Erdem AKOĞLU[1*]**
[1]Niğde Ömer Halisdemir University, Faculty of Sports Sciences, Niğde, Türkiye

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## Abstract

This research aimed to contribute to the literature by targeting consumers with real chatbot experiences in purchasing sports products and services, addressing the cognitive and emotional processes that influence consumer decisions within the Stimulus-Organism-Response (S-O-R) framework. The proposed model was grounded in the S-O-R theory and the Information Acceptance Model. It examines the impact of AI-generated information (e.g., quality, credibility, usefulness, and adoption) and utilitarian features (e.g., convenience, choice, information accessibility) on psychological ownership, ease of use, trust in AI, and purchase intention. Datas were collected from 552 consumers with chatbot experience. the findings showed that the perceived value of chatbot-generated information and utilitarian features significantly affect users' psychological ownership and ease of use. These internal responses, in turn, significantly influence trust in AI and purchase intentions. Structural equation modelling validated the mediating roles of psychological ownership and ease of use. Additionally, perceived intelligence of AI moderated the strength of these relationships, with higher intelligence perceptions weakening emotional and intuitive connections. The study provides practical guidance for brands on how to design chatbot systems that enhance user control, foster emotional engagement, and increase purchase intentions. Customization, intuitive interfaces, and demographic-based strategies are recommended. This is one of the first studies to integrate S-O-R and Information Acceptance Models to explore AI-powered chatbot influence in sports e-commerce, revealing unique psychological mechanisms and moderation effects in consumer decision-making.
**Keywords**: Chatbots, S-O-R, Artificial intelligence, Consumer, Purchase intention

[*] **Corresponding Author:** Halil Erdem AKOĞLU, **E-mail:** erdemakoglu@hotmail.com

## INTRODUCTION

In recent years, artificial intelligence (AI) technologies have become an important factor that directly influences consumer behavior and causes businesses to radically transform their marketing strategies. In particular, AI-based chatbots and other applications in the fields of online retail and digital sports marketing have reshaped how brands interact with consumers (Mohammadi et al., 2025). Chatbots are transforming the customer experience and providing brands with significant competitive advantages through functions such as providing information to consumers, recommending products, and facilitating the shopping process (Bhagat et al., 2023; Luo et al., 2019).

This technological transformation necessitates a reassessment of consumer behavior not only in cognitive terms but also in psychological and emotional dimensions. In this context, the Stimulus-Organism-Response (S-O-R) model provides a theoretical foundation for understanding the transformation caused by AI-driven external stimuli (e.g., information quality, information reliability, information usability) in consumers' internal mental states (psychological ownership, ease of use) and the behavioral responses (trust, purchase intention) (Mehrabian & Russell, 1974; Jacoby, 2002). Additionally, the Information Adoption Model (IAM) and the utilitarian value theory also complement the explanation of consumers' responses to AI-based information (Erkan & Evans, 2016; To et al., 2007). Moreover, the perception of how "intelligent" AI systems are perceived by consumers has been considered as a moderating factor in these relationships. This is because perceiving the system as overly intelligent can reduce consumers' sense of control, thereby weakening positive effects such as psychological ownership or ease of use (Jin & Youn, 2023; Lopes et al., 2024).

The main objective of this study is to analyze how the information provided by AI-supported chatbots and the utilitarian features of these systems affect consumers' psychological and cognitive evaluations and how this reflects on their purchase intentions. The research aims to provide insights based on real experiences by targeting consumers who have had chatbot experiences when purchasing sports products and services. In this regard, the research aims to contribute to the literature by comprehensively addressing the cognitive and emotional processes that influence consumer decisions within the framework of the S-O-R model.

## BACKGROUND LITERATURE AND HYPOTHESIS DEVELOPMENT

### Stimulus-Organism-Response (S-O-R)

The S-O-R theory was first proposed by Mehrabian and Russell (1974). The model was later developed by Jacoby (2002), who approached consumer behavior modeling in a more innovative and integrative way. The S-O-R model, designed on the basis of environmental psychology, states that environmental stimuli (stimulus) affect an individual's internal state (organism) and lead to behavioral responses (response) (Mehrabian & Russell, 1974). Accordingly, the S-O-R model consists of three elements: stimulus, organism, and response. The stimulus element refers to external factors that influence individuals' internal states and affect their behavior (Zhou et al., 2022). The organism element refers to the cognitive and emotional state that expresses individuals' internal mental processes. This element acts as an intermediary between environmental stimuli and individuals' behavioral actions (Cheng et al., 2021; Zhu et al., 2023). The response element refers to behavioral responses that arise as a result of the internal state being affected by the stimulating effect of environmental factors (Armutcu et al., 2024). In this study, the stimulus elements considered information provided by artificial intelligence (information quality, information credibility, information usefulness, information adoption) and the utilitarian values of artificial intelligence (convenience, selection, information availability). Previous studies have extensively used these variables as stimuli that affect consumers' internal states (Biswas et al., 2025; Elayat & Elalfy, 2025; Zhu et al., 2023). Therefore, the information obtained from chatbots will affect consumers as an external stimulus and influence their internal state, these variables have been assigned as stimuli. Consumers who evaluate the utilitarian value of chatbot information and the perceived value of information generated by the chatbot develop both internal psychological responses (psychological ownership) (Kang et al., 2024) and cognitive function-oriented responses (ease of use). The perception of ease of use has generally been evaluated as an external stimulus in previous studies (Dahri et al., 2025, Xu et al., 2024) particularly within the framework of the Technology Acceptance Model (TAM) (Davis, 1989). The reason for evaluating it as an organism in this study is that AI usability is not a fixed environmental feature but a subjective psychological evaluation that emerges after interacting with AI-supported systems. This is because usability reflects users' internalized perceptions of how intuitive the system is from their own cognitive perspectives (Gefen & Straub, 2000). Furthermore, when evaluated through Lazarus (1991) cognitive evaluation theory approach, ease of use is a more appropriate element for the organism because it reflects a cognitive evaluation influenced by external stimuli such as interface visibility and recommendation relevance. Psychological ownership and ease of use, which are considered psychological and cognitive variables and are elements of the organism, emerge as trust in artificial intelligence (Shan & Li, 2025) and purchase intention (Han et al., 2022; Zhu et al., 2020) in customers. The S-O-R model has also been frequently addressed in previous technology-based consumer behavior studies (Biswas et al., 2025; Vafaei-Zadeh et al., 2024; Zhu et al., 2023). Therefore, this model was chosen as the basis for our research as it provides the most appropriate foundation for our study.

## Utilitarian Values

Utilitarian value reflects the task-oriented, functional benefits consumers derive from shopping experiences (Babin et al., 1994; Vieira et al., 2022). These values emphasize efficiency, goal completion, and usefulness throughout the shopping process (To et al., 2007). While To et al. originally identified six utilitarian dimensions, this study focuses on three that align with AI-supported shopping contexts: convenience, selection, and information availability. These aspects are directly relevant to how consumers interact with chatbot-based virtual assistants and how such systems streamline product selection and information access.

Prior research shows that utilitarian elements—particularly those facilitating autonomy and efficiency—enhance users' psychological ownership and perceptions of ease of use (Cheng, 2022). When consumers experience functional control over the process, they are more likely to internalize the system and feel competent using it (D'Souza et al., 2023; Pierce et al., 2003). Accordingly, the following hypotheses are proposed:

**H1:** Utilitarian values positively influence both psychological ownership **(H1a)** and the perceived ease of use of AI-supported systems **(H1b).**

**Information Acceptance Model**

The Information Acceptance Model (IACM), developed by Erkan and Evans (2016), integrates elements of the Information Adoption Model (Sussman & Siegal, 2003) and the Theory of Reasoned Action (TRA; Ajzen & Fishbein, 1975) to explain how consumers evaluate eWOM information and form purchase intentions. While IAM focuses on information characteristics such as quality and credibility, TRA contributes by incorporating behavioral intentions, resulting in a more comprehensive understanding of information processing. In this study, the IACM was adapted to the context of chatbot-generated information. Specifically, the model considers four key dimensions: information quality, credibility, usefulness, and adoption. Prior research indicates that high-quality and reliable information fosters psychological ownership toward the system providing it (Chan et al., 2024). When users perceive AI-generated content as useful and aligned with their needs, they are more likely to feel that the system belongs to them (Pierce et al., 2003) and to perceive it as easier to use (Abdullah et al., 2016; Tseng & Wu, 2024). Although these relationships have not been extensively tested in AI contexts, theoretical perspectives suggest that valuable information enhances both psychological ownership and ease of use. Therefore, the following hypotheses are proposed:

**H2**: The perceived value of AI-generated information positively affects psychological ownership (**H2a**) and the perceived ease of use of AI systems (**H2b**).

Psychological ownership is defined as "a situation in which individuals feel that their ownership goal belongs to them" (Pierce et al., 2003). This perceived sense of possession leads individuals to develop emotional attachment and responsibility toward the object (Morewedge, 2021). Psychological ownership has been widely studied across various domains such as tourism, fashion, and consumer electronics (D'Souza et al., 2023; Qu et al., 2021). With the increasing integration of artificial intelligence into everyday life, this concept has gained relevance in human-AI interactions (Malhotra et al., 2022). For instance, Jin and Youn (2023) examined how psychological ownership drives engagement with AI-powered chatbots, while Scarpi (2024) xplored its role in tourism-related chatbot services. As AI agents increasingly replace traditional sales representatives, understanding the antecedents of trust toward such systems has become essential (Kim & Song, 2023). Hu et al. (2025) found that a strong sense of psychological ownership toward chatbots enhances consumer trust.

Moreover, research indicates that psychological ownership fosters identification with products and services, thereby increasing purchase intentions (Pham et al., 2024; Wahab et al., 2022). Based on this evidence, the following hypotheses are proposed:

**H3.** Psychological ownership positively affects both trust in artificial intelligence (**H3a**) and purchase intention (**H3b**).

**AI Enabled Ease of Use**

Ease of use refers to the degree to which a person can use a particular technology effortlessly (Davis, 1989). In the context of AI-supported shopping, it reflects the consumer's belief that less effort is required to complete tasks (Bhagat et al., 2023). Prior research has highlighted the importance of ease of use in reducing uncertainty and encouraging adoption of internet-based services (Sarkar et al., 2020; Sboui et al., 2024). It also plays a key role in building initial trust in chatbots (Mostafa & Kasamani, 2022).

Furthermore, ease of use not only fosters trust in AI but also positively influences consumer purchase decisions by reducing perceived complexity and enhancing usability (Filipović & Šapić, 2025; Luo et al., 2019). Based on this literature, the following hypotheses were proposed:

**H4.** The ease of use of artificial intelligence positively influences both trust in AI **(H4a)** and purchase intention **(H4b)**.

**Trust in AI**

"Trust is defined as a general belief that a person will behave in accordance with positive expectations toward a trusted person" (Gefen, 2000). Grazioli and Jarvenpaa (2000) define trust as "a perceived state of vulnerability or risk arising from uncertainty about the motivations, intentions, and possible actions of others on whom one depends." In addition to these definitions in the field of social psychology, trust plays an important role for consumers in their interactions with smart technologies and in the online shopping environment (Malhotra & Ramalingam, 2025). The uncertainties inherent in online shopping—such as concerns about the seller's reputation or security—make consumer trust particularly important (Kasilingam, 2020). Trust is the most fundamental requirement for consumers who use online shopping services to perceive the value of the service positively or negatively. Therefore, it influences consumers' decision-making and purchasing behavior (ElSayad & Mamdouh, 2024; Zhang et al., 2024). Therefore, the following hypothesis is proposed:

**H5.** Trust in artificial intelligence positively influences purchase intention.

### Mediation Effects

Consumer behavior is influenced not only by external stimuli—such as utilitarian values and the perceived value of AI-generated information—but also by internal evaluations like psychological ownership and perceived ease of use (Mehrabian & Russell, 1974). These internal mechanisms may mediate the effects of external stimuli on trust in AI and purchase intention. Prior research indicates that utilitarian benefits (To et al., 2007; Vieira et al., 2022) and information quality (Erkan & Evans, 2016) enhance users' sense of ownership and ease of system use, which in turn shape trust and purchasing behavior (Bhagat et al., 2023). Therefore, the following hypotheses have been developed:

**H6.** Psychological ownership (**H6a**) and AI ease of use (**H6b**) mediate the relationship between utilitarian values and trust in AI, while both also mediate the relationship between utilitarian values and purchase intention (**H6c**, **H6d**).

**H7.** Psychological ownership (**H7a**) and AI ease of use (**H7b**) mediate the relationship between the perceived value of AI-generated information and trust in AI, as well as their relationship with purchase intention (**H7c**, **H7d**).

### The Moderating Role of Perceived Intelligence

The way consumers perceive the intelligence level of AI systems can significantly influence their behavior. Intelligence is defined as a system's ability to learn, reason, and solve problems (Bartneck et al., 2009), and is typically assessed through indicators such as competence, efficiency, and output effectiveness (Le, 2023). Chatbots possess sufficient cognitive functionality to handle user queries, facilitate tasks like payments, and sustain interactive dialogues (Krishnan et al., 2022). However, perceiving AI as highly intelligent may elevate user expectations while simultaneously reducing their perceived control, thus weakening the effects of psychological ownership and intuitive ease of use (Jin & Youn, 2023; Lopes et al., 2024). This dynamic can place users in a more passive role, diminishing their sense of system ownership and the influence of ease of use on purchase intention (Malhotra & Ramalingam, 2025). Therefore, the following hypotheses have been developed:

**H8:** Perceived intelligence moderates the effect of psychological ownership on both trust in AI **(H8a)** and purchase intention **(H8b)**.

**H9:** Perceived intelligence moderates the effect of AI ease of use on both trust in AI (**H9a**) and purchase intention (**H9b**).

## METHOD

### Research Model

This study uses a quantitative research design based on the Stimulus-Organism-Response (SOR) framework to investigate the impact of AI-generated information on consumers' psychological mechanisms and behavioral intentions in the context of consumers purchasing sports products and services (Figure 1).

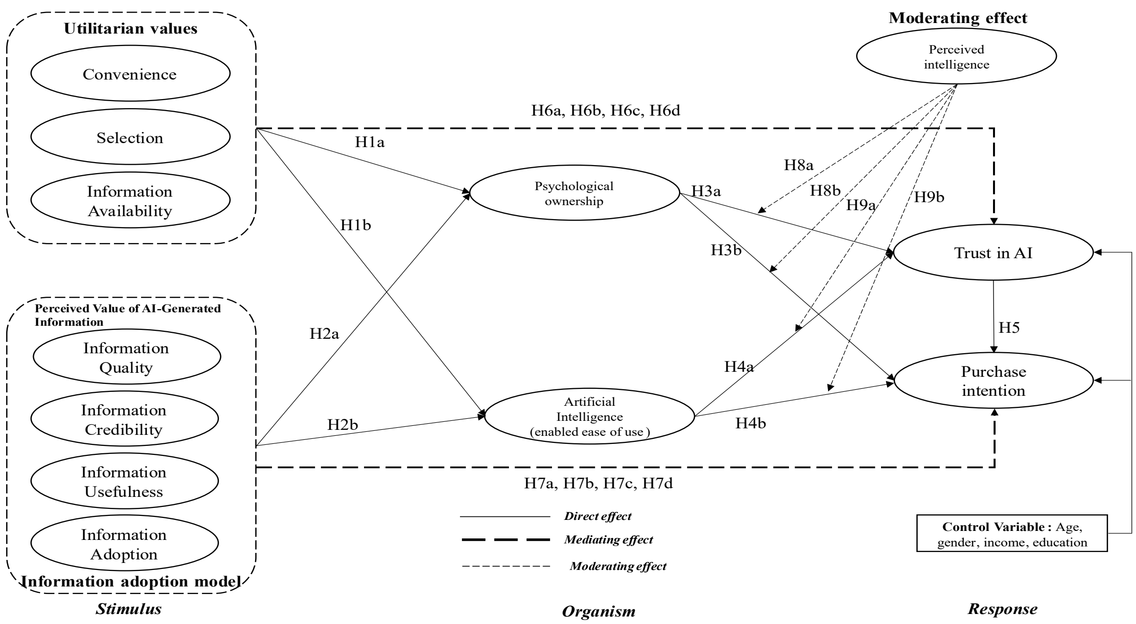


**Figure 1:** Research model
**Source(s):**Authors'own work

### Sampling and Data Collection

The final sample consisted of 552 consumers who had engaged in transactions with businesses offering sports products or services through AI-assisted chatbots or virtual assistants. The sampling frame included prominent sports brands such as Nike (Nike Virtual Assistant), Adidas (Adi Bot), and Under Armour (UA Record), as well as leading digital retail platforms like Amazon, Hepsiburada, and Trendyol, all of which incorporate AI-driven customer service agents into their digital ecosystems. A purposive sampling strategy was employed to ensure that participants had relevant and direct experience with AI-supported retail environments. To enhance the validity of the data, a two-stage screening procedure was implemented. Initially, participants were asked: (1) "Have you used a virtual assistant or chatbot while shopping?" and (2) "Which of the following AI-assisted platforms have you purchased from?" Only respondents who affirmed the first question and identified at least one of the study-relevant AI-integrated platforms in the second question were retained in the final dataset. This screening mechanism ensured that the dataset comprised individuals with authentic and first-hand experience interacting with AI-supported interfaces during their shopping journey, thereby enhancing the relevance and reliability of the findings within the context of AI-assisted sports retail environments.

An analysis of the participants' demographic characteristics revealed that the sample consisted of 56.89% male (n = 297) and 43.11% female (n = 225) consumers. Regarding educational attainment, the majority of participants were undergraduate degree holders (62.26%; n = 325), followed by high school graduates (28.54%; n = 149) and postgraduate degree holders (9.20%; n = 48). The average monthly income of the participants was 51,445 TL, and their mean age was calculated as 23.38 years. These findings indicate that the sample predominantly consisted of young and well-educated consumers.

**Measurement Instrument**

Data were collected online via a structured questionnaire designed through Google Forms. Scale items were adapted from validated sources and tailored to AI-enabled sport product consumption. Utilitarian values (convenience, choice, information availability) were adapted from To et al. (2007), while perceived value of AI knowledge (information quality, reliability, usefulness, adoption) was based on Erkan and Evans (2018). Other constructs included psychological ownership (Cheng, 2022), AI ease of use and purchase intention (Bhagat et al., 2023), and perceived intelligence and AI trust (Bhagat et al., 2023), and perceived intelligence and AI trust (Malhotra & Ramalingam, 2025). All items were measured on a 7-point Likert scale. The questionnaire was translated into Turkish, reviewed by three language experts, and revised based on feedback from two marketing professors. A pilot study (n = 30) confirmed item clarity. These procedures, aligned with Akoğlu et al. (2024) and (Kumar & Hsieh, 2024), ensured face and content validity.

**Ethical Approval**

The study was approved by Niğde Ömer Halisdemir University Ethics Committee (Date=27/05/2025-Number=09) and was conducted according to the principles stated in the Declaration of Helsinki.

**Common Method Bias**

To minimize common method bias (CMB), both procedural and statistical remedies were applied (Podsakoff et al., 2003). Methodologically, validated scales were adapted, participant anonymity was assured, and a pilot study (n=30) ensured item clarity. Statistically, Harman's single-factor test showed that the first factor explained 32.1% of the variance—below the 50% threshold (Podsakoff et al., 2012). Additionally, a latent method factor was included in the model; its loadings were low and non-significant, and original factor loadings remained stable (Kock, 2015), confirming that CMB was not a significant concern.

**Data Analysis**

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0, which is suitable for complex models involving formative and reflective constructs and when the research aims to predict key target constructs (Hair et al., 2017). Prior to hypothesis testing, a two-step approach was applied, consisting of measurement model evaluation and structural model assessment (Hair et al., 2019). In the data analysis process, the measurement model was first evaluated; in this context, standard factor loadings, Cronbach's Alpha, and composite reliability (CR) were calculated for reliability, and average explained variance (AVE), Fornell-Larcker criterion, and HTMT ratio were calculated for validity. Then, structural model analysis was performed, and path coefficients, explained variance ($R^2$), prediction accuracy ($Q^2$), and effect size *($f^2$)* were analyzed. Additionally, indirect effects were tested using the bootstrap method for mediation effects, and the VAF (Variance Accounted For) value was calculated to determine the type of mediation. In the moderator effect analysis, interaction terms were used to test the moderating effect of perceived artificial intelligence. Finally, demographic variables such as age, gender, education, and income were included in the model as control variables.

## FINDINGS

### Measurement model

**Table 1.** Construct reliability and convergent validity indicators

| Constructs | Items | SFL (>0.7) | Cronbach's alpha (>0.7) | Composite reliability (> 0.7) | AVE (> 0.5) |
|---|---|---|---|---|---|
| Convenience | C1<br>C2<br>C3<br>C4 | 0,788<br>0,834<br>0,841<br>0,822 | 0,904 | 0,933 | 0,777 |
| Selection | S1<br>S2<br>S3 | 0,874<br>0,873<br>0,847 | 0,924 | 0,952 | 0,867 |
| Information availability | IA1<br>IA2<br>IA3<br>IA4 | 0,863<br>0,845<br>0,839<br>0,845 | 0,922 | 0,945 | 0,811 |
| Information quality | IQ1<br>IQ2<br>IQ3<br>IQ4<br>IQ5 | 0,815<br>0,820<br>0,818<br>0,835<br>0,846 | 0,924 | 0,942 | 0,766 |
| Information credibility | IC1<br>IC2<br>IC3<br>IC4 | 0,819<br>0,844<br>0,811<br>0,818 | 0,903 | 0,932 | 0,774 |
| Information usefulness | IU1<br>IU2 | 0,840<br>0,824 | 0,898 | 0,951 | 0,907 |
| Information adoption | BA1<br>BA2<br>BA3<br>BA4 | 0,838<br>0,793<br>0,801<br>0,765 | 0,906 | 0,935 | 0,782 |
| Psychological ownership | PS1<br>PS2<br>PS3 | 0,913<br>0,940<br>0,909 | 0,911 | 0,944 | 0,848 |
| Artificial intelligence (enabled ease of use) | AI1<br>AI2<br>AI3 | 0,917<br>0,930<br>0,909 | 0,907 | 0,942 | 0,844 |
| Artificial intelligence trust | TAI1<br>TAI2<br>TAI3 | 0,909<br>0,920<br>0,895 | 0,894 | 0,934 | 0,825 |
| Perceived intelligence | PA1<br>PA2<br>PA3<br>PA4 | 0,846<br>0,830<br>0,873<br>0,875 | 0,879 | 0,916 | 0,733 |
| Purchase intention | PI1<br>PI2<br>PI3 | 0,920<br>0,947<br>0,928 | 0,924 | 0,952 | 0,867 |

**Note(s):** AVE: average variance extracted, SFL: standardized factor loadings

Table 1 presents standardized factor loadings (SFL), Cronbach's Alpha, composite reliability (CR), and average variance extracted (AVE) values. All factor loadings exceed 0.70, indicating strong item reliability (Hair et al., 2019). Cronbach's Alpha and CR values are above the 0.70 threshold, confirming high internal consistency (George & Mallery, 2024). AVE values also surpass 0.50, supporting convergent validity (Fornell & Larcker, 1981).

**Table 2.** Discriminant validity (Fornell-Larcker criterion)

| Constructs | C | S | IA | IQ | IC | IU | IAP | PO | AIEAU | AIT | PEI | PUI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Convenience | **0.882** | | | | | | | | | | | |
| Selection | 0.808 | **0.931** | | | | | | | | | | |
| Information availability | 0.804 | 0.819 | **0.900** | | | | | | | | | |
| Information quality | 0.701 | 0.710 | 0.793 | **0.875** | | | | | | | | |
| Information credibility | 0.617 | 0.618 | 0.701 | 0.863 | **0.880** | | | | | | | |
| Information usefulness | 0.690 | 0.731 | 0.737 | 0.771 | 0.782 | **0.884** | | | | | | |
| Information adoption | 0.625 | 0.651 | 0.725 | 0.776 | 0.762 | 0.775 | **0.952** | | | | | |
| Psychological ownership | 0.546 | 0.578 | 0.672 | 0.608 | 0.572 | 0.572 | 0.536 | **0.921** | | | | |
| Artificial intelligence (enabled ease of use) | 0.687 | 0.751 | 0.752 | 0.742 | 0.701 | 0.797 | 0.715 | 0.585 | **0.919** | | | |
| Artificial intelligence trust | 0.570 | 0.558 | 0.609 | 0.703 | 0.714 | 0.701 | 0.720 | 0.575 | 0.645 | **0.908** | | |
| Perceived intelligence | 0.573 | 0.555 | 0.635 | 0.719 | 0.731 | 0.691 | 0.680 | 0.548 | 0.684 | 0.753 | **0.856** | |
| Purchase intention | 0.807 | 0.856 | 0.819 | 0.711 | 0.618 | 0.731 | 0.651 | 0.577 | 0.751 | 0.558 | 0.556 | **0.931** |

∗ *Root square of AVE*

Discriminant validity was assessed using the Fornell-Larcker criterion and the HTMT ratio. According to Fornell and Larcker (1981)), the square root of AVE for each construct should exceed its correlations with other constructs. As shown in Table 2 and 3, this condition is met, indicating conceptual distinctiveness among constructs. Additionally, the HTMT (Heterotrait-Monotrait Ratio) was used as a more sensitive measure (Henseler et al., 2015). All HTMT values were below the 0.90 threshold, further confirming discriminant validity across variables.

**Table 3.** Heterotrait-Monotrait Ratio (HTMT)

| Constructs | C | S | IA | IQ | IC | IU | IAP | PO | AIEAU | AIT | PEI | PUI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Convenience | | | | | | | | | | | | |
| Selection | 0.883 | | | | | | | | | | | |
| Information availability | 0.880 | 0.887 | | | | | | | | | | |
| Information quality | 0.768 | 0.770 | 0.860 | | | | | | | | | |
| Information credibility | 0.683 | 0.676 | 0.768 | 0.945 | | | | | | | | |
| Information usefulness | 0.760 | 0.797 | 0.803 | 0.841 | 0.862 | | | | | | | |
| Information adoption | 0.693 | 0.715 | 0.796 | 0.852 | 0.846 | 0.857 | | | | | | |
| Psychological ownership | 0.599 | 0.626 | 0.733 | 0.662 | 0.629 | 0.627 | 0.591 | | | | | |
| Artificial intelligence (enabled ease of use) | 0.758 | 0.820 | 0.822 | 0.811 | 0.775 | 0.877 | 0.792 | 0.642 | | | | |
| Artificial intelligence trust | 0.634 | 0.614 | 0.671 | 0.773 | 0.795 | 0.778 | 0.803 | 0.638 | 0.716 | | | |
| Perceived intelligence | 0.641 | 0.616 | 0.703 | 0.796 | 0.820 | 0.772 | 0.764 | 0.612 | 0.766 | 0.850 | | |
| Purchase intention | 0.883 | 0.836 | 0.887 | 0.770 | 0.676 | 0.797 | 0.715 | 0.626 | 0.820 | 0.614 | 0.616 | |

**Assessment of the formative construct**

Utilitarian values and AI knowledge were modeled as second-order reflective–formative constructs. This approach is appropriate when conceptually related first-order dimensions load onto a broader latent construct (Hair et al., 2019), offering model simplicity and addressing multicollinearity (Podsakoff et al., 2003). To evaluate the formative structure, VIF values and indicator weights were analyzed (Table 4). All VIF values were below the threshold of 5 (Hair et al., 2011), indicating no multicollinearity. Using bootstrapping with 5000 resamples, all indicator weights were found to be significant at the $p < 0.001$ level. Based on these results, the three-dimensional utilitarian values and four-dimensional AI knowledge constructs were reduced to single higher-order factors for further analysis.

**Table 4.** Assessment of higher-order construct

| Higher-Order Constructs | Paths | *β* | t | *p* | LLCI | ULCI | VIF |
|---|---|---|---|---|---|---|---|
| Utilitarian values | Convenience | 0.357 | 50.678 | 0.000 | 0.343 | 0.370 | 3.491 |
| | Selection | 0.307 | 49.241 | 0.000 | 0.295 | 0.320 | 3.756 |
| | Information Availability | 0.405 | 54.574 | 0.000 | 0.392 | 0.421 | 3.688 |
| AI information | Information Quality | 0.358 | 55.976 | 0.000 | 0.346 | 0.371 | 4.649 |
| | Information Credibility | 0.281 | 55.970 | 0.000 | 0.271 | 0.291 | 4.623 |
| | Information Usefulness | 0.158 | 40.802 | 0.000 | 0.150 | 0.165 | 3.287 |
| | Information Adoption | 0.288 | 50.807 | 0.000 | 0.277 | 0.300 | 3.302 |

**Structural model**

Following the confirmation of the measurement model, the structural model was evaluated using key criteria: path coefficient significance, explained variance ($R^2$), predictive relevance ($Q^2$), and effect size ($f^2$). Table 5 presents the direct effects from the PLS analysis. Utilitarian values significantly impact psychological ownership ($\beta = 0.398$, $p < 0.001$) and AI ease of use ($\beta = 0.372$, $p < 0.001$), supporting H1a and H1b. Similarly, perceived value of AI information positively affects both psychological ownership ($\beta = 0.305$, $p < 0.001$) and AI ease of use ($\beta = 0.502$, $p < 0.001$), supporting H2a and H2b. Psychological ownership and AI ease of use significantly influence AI trust ($\beta PO = 0.308$, $\beta AIEU = 0.464$, both $p < 0.001$) and purchase intention ($\beta PO = 0.191$, $\beta AIEU = 0.579$, both $p < 0.001$), confirming H3a, H3b, H4a, and H4b. However, AI trust does not significantly affect purchase intention ($\beta = 0.064$, $p = 0.234$), and thus H5 is not supported.

**Table 5.** The direct effects.

| Hyp | Paths | *β* | t | *p* | LLCI | ULCI | Supported? |
|---|---|---|---|---|---|---|---|
| H1a | *UV→PO* | 0,398 | 4,550 | 0,000 | 0,238 | 0,572 | Yes |
| H1b | *UV→AIEU* | 0,372 | 6,209 | 0,000 | 0,258 | 0,490 | Yes |
| H2a | *AII→ PO* | 0,305 | 3,772 | 0,000 | 0,144 | 0,455 | Yes |
| H2b | *AII→ AIEU* | 0,502 | 8,070 | 0,000 | 0,380 | 0,618 | Yes |
| H3a | *PO→AIT* | 0,308 | 7,084 | 0,000 | 0,224 | 0,388 | Yes |
| H3b | *PO→PI* | 0,191 | 4,137 | 0,000 | 0,102 | 0,279 | Yes |
| H4a | *AIEU →AIT* | 0,464 | 10,376 | 0,000 | 0,373 | 0,550 | Yes |
| H4b | *AIEU →PI* | 0,579 | 11,374 | 0,000 | 0,470 | 0,674 | Yes |
| H5 | *AIT→PI* | 0,064 | 1,192 | 0,234 | -0,043 | 0,180 | No |

UV= Utilitarian values; AII= AI information PO = Psychological Ownership; AIEAU = Artificial Intelligence (Enabled Ease of Use); AIT = Artificial Intelligence Trust; PEI = Perceived Intelligence; PUI = Purchase Intention.

## Mediating effects

We examined the mediating roles of psychological ownership and AI-enabled ease of use using the bootstrapping method with 5000 re-samples and 95% confidence intervals (Preacher & Hayes, 2008). Mediation significance was assessed through indirect effects, followed by the VAF (Variance Accounted For) method to determine mediation type. VAF values below 20% indicate no mediation, 20–80% partial mediation, and above 80% full mediation.(Hair et al., 2017; Zhao et al., 2010). According to Table 6, utilitarian values affect AI trust (β=0.122, p<.001) and purchase intention (β=0.079, p=.018) via psychological ownership, with VAFs of 41% and 25%, indicating partial mediation (H6a, H6b supported). Similarly, utilitarian values influence AI trust (β=0.172, p<.001) and purchase intention (β=0.217, p<.001) through ease of use, with VAFs of 58% and 70% (H6c, H6d supported).

Perceived information value impacts AI trust (β=0.233, p<.001) and purchase intention (β=0.057, p<.001) via psychological ownership, with partial mediation for trust (71%) and no mediation for intention (15%) (H7a, H7b supported). Lastly, ease of use mediates the effect of information value on both AI trust (β=0.234) and purchase intention (β=0.290), confirming partial mediation (H7c, H7d supported).

**Table 6.** The mediation effects

| Hyp | Paths | *β* | t | *p* | LLCI | ULCI | VAF | Result | Med.? |
|---|---|---|---|---|---|---|---|---|---|
| H6a | *UV→PO→ AIT* | 0.122 | 4,422 | 0,000 | 0,073 | 0,180 | 41% | Supported | Partial |
| H6b | *UV→PO→PI* | 0,079 | 2,376 | 0,018 | 0,027 | 0,150 | 25% | Supported | Partial |
| H6c | *UV→ AIEU → AIT* | 0,172 | 5,729 | 0,000 | 0,158 | 0,314 | 58% | Supported | Partial |
| H6d | *UV→ AIEU →PI* | 0,217 | 4,725 | 0,000 | 0,135 | 0,315 | 70% | Supported | Partial |
| H7a | *AII →PO→ AIT* | 0,233 | 5,784 | 0,000 | 0,036 | 0,163 | 71% | Supported | Partial |
| H7b | *AII →PO→PI* | 0,057 | 3,582 | 0,000 | 0,027 | 0,090 | 15% | Supported | No |
| H7c | *AII → AIEU → AIT* | 0,234 | 5,784 | 0,000 | 0,158 | 0,314 | 71% | Supported | Partial |
| H7d | *AII → AIEU →PI* | 0,290 | 7,327 | 0,000 | 0,222 | 0,370 | 78% | Supported | Partial |

UV= Utilitarian values; AII= AI information PO = Psychological Ownership; AIEAU = Artificial Intelligence (Enabled Ease of Use); AIT = Artificial Intelligence Trust; PEI = Perceived Intelligence; PUI = Purchase Intention.

## Moderation effects

Table 7 analyzes the moderating role of perceived AI intelligence (PEI) on the relationships between psychological ownership (PO), AI ease of use (AIEU), and trust in AI (TAI) with purchase intention (PUI). The interaction POPEI → PUI is significant (β = -0.093, t = 4.141, p < 0.001), indicating that as AI is perceived as more intelligent, the impact of PO on PUI diminishes. Similarly, the interaction AIEUPEI → PUI is significant (β = -0.081, t = 3.786, p < 0.001), showing that perceived intelligence weakens the positive effect of ease of use on purchase intention. The same trend is observed in the TAI*PEI → PUI path (β = -0.074, t = 3.200, p = 0.001), where trust becomes less impactful as perceived intelligence increases.

**Table 7.** The (conditional) moderating effects

| Hyp | Paths | *β* | t | *p* | LLCI | ULCI | Supported? |
|---|---|---|---|---|---|---|---|
| | *PO→PI conditional on PEI at +1 SD* | 0.122 | 2.188 | 0,029 | 0,059 | 0,261 | |
| H8a | *PO→PI conditional on PEI at mean* | 0.197 | 4.794 | 0.000 | 0.113 | 0.273 | Supported |
| | *PO→PI conditional on PEI at -1 SD* | 0.272 | 4.006 | 0.000 | 0.149 | 0.407 | |
| | *AIEU →PI conditional on PEI at +1 SD* | 0.597 | 8.088 | 0.000 | 0.447 | 0.735 | |
| H8b | *AIEU →PI conditional on PEI at mean* | 0.621 | 12.100 | 0.000 | 0.506 | 0.712 | Supported |
| | *AIEU →PI conditional on PEI at -1 SD* | 0.644 | 9.739 | 0.000 | 0.502 | 0.760 | |

Table 7 presents the moderation analysis of perceived intelligence (PEI) on the relationships between psychological ownership (PO), AI ease of use (AIEU), and purchase intention (PI). Conditional effects were examined at low (-1 SD), mean, and high (+1 SD) levels of PEI. Findings indicate that PEI significantly moderates the PO–PI relationship. The effect is strongest when PEI is low ($\beta = 0.272$, $p < .001$) and weaker at high PEI ($\beta = 0.122$, $p = .029$), suggesting that higher PEI weakens the impact of PO on PI. Similarly, PEI also moderates the AIEU–PI relationship, with stronger effects at low PEI ($\beta = 0.644$) compared to high PEI ($\beta = 0.597$), though both remain significant ($p < .001$). Figure 4 illustrates these interactions via slope analysis. Overall, PEI served as a statistically significant attenuating moderator in both relationships.


**Figure 2.** Conditional moderation effects of PO and AIEU on PI across PEI levels

## Control variables

In the study, we used control variables to reduce confounding effects, increase the explanatory power of the model and test the unique effect of the relationships. In our study, age, education, gender and average monthly income variables were used as control variables. The control variables did not have a statistically significant effect on the structural paths and it was revealed that there was no confounding effect and the model was generalizable.

**Predictive Power**

The analysis reports $R^2$, $Q^2$, and $f^2$ values to assess the model's explanatory and predictive power. The $R^2$ values indicate that psychological ownership (44.6%), AI ease of use (69.5%), trust in AI (48.9%), and purchase intention (60.9%) are well explained, reflecting medium to high explanatory power (Hair et al., 2017). Based on Stone (1974) and Geisser (1974), all endogenous constructs demonstrated significant predictive relevance ($Q^2 > 0$). Effect size ($f^2$) values, evaluated using Cohen (1988) thresholds, show that AI ease of use has a large effect on purchase intention ($f^2 = 0.366$), with varying effects among other variables (see Table 8).

**Table 8.** Model's explanatory and predictive power and effect sizes

| | **PS** | **AII** | **AIT** | **PI** |
|---|---|---|---|---|
| $R^2$ | 0.446 | 0.695 | 0.489 | 0.609 |
| $Q^2$ | 0.371 | 0.582 | 0.396 | 0.517 |
| $f^2$ | | | | |
| **UV** | 0.095 | 0.154 | | |
| **AII** | 0.058 | 0.283 | | |
| **PO** | | | 0.123 | 0.053 |
| **ATEU** | | | 0.274 | 0.366 |
| **AIT** | | | | 0.005 |

UV= Utilitarian values; AII= AI information PO = Psychological Ownership; AIEAU = Artificial Intelligence (Enabled Ease of Use); AIT = Artificial Intelligence Trust; PEI = Perceived Intelligence; PUI = Purchase Intention.

## DISCUSSION

This research study aims to examine the impact of artificial intelligence-supported chatbot systems on consumers' psychological and cognitive evaluations within the Stimulus-Organism-Response (S-O-R) framework and to explain how these effects influence purchase intention. The findings indicate that the value and utilitarian characteristics of information generated by chatbots enhance consumers' psychological ownership of the chatbots and their perception of ease of use. The study also shows that these perceptions significantly affect consumers' trust in artificial intelligence and their purchase intention.

The research findings demonstrate that the utilitarian values perceived by consumers toward sports product or service brands with chatbot systems have a positive effect on their psychological ownership and perceived ease of use of the systems. Li et al. (2023) demonstrated that the perception of convenience, information access, and control provided by chatbots increases users' ongoing intention to use these systems through perceived utility value. Zhang et al. (2025) discovered that when users have the capacity to actively select their chatbot avatars, there is a substantial increase in their psychological sense of ownership. Similarly, Kim and Kim (2024) eported that the benefits provided by expert system-based assistants trigger a sense of psychological ownership in users, which in turn positively affects their perceived ease of use of the system. These studies support the results of our research.

The perceived value of AI-generated information, i.e., quality, credibility, usefulness, and adoption, also positively influences psychological ownership and the perceived ease of use of AI. Although the perceived value of information and its relationship to psychological ownership and ease of use has not been directly measured in previous literature, some indicators such as "value congruence" in idea generation processes and LLM interface quality can be considered indirect proxies for information quality (Guo et al., 2024; Xu et al., 2024). For instance, Guo et al. (2025) show that both psychological ownership and ease of use perception can be jointly addressed in argument interfaces by designing large language model-supported (LLM) user interfaces.

Psychological ownership and perceived ease of use of AI as organismic factors strongly affect trust in AI and consumers' purchase intention. The effect of psychological ownership on trust in AI aligns with the findings of Hu et al. (2025) and Kim et al. (2021). Likewise, the positive effect of psychological ownership on purchase intention is supported by previous research (Pick, 2021; Sehgal et al., 2023). The perceived ease of use of AI has a strong impact on trust in AI. These findings are consistent with the results of Choung et al. (2023) and Sboui et al. (2024). Furthermore, the effect of perceived ease of use on consumers' purchase intentions aligns with several prior studies (Arachchi & Samarasinghe, 2023; Lopes et al., 2024). Shin and Yang (2025) onducted a study on Chinese consumers and found that consumers' perception of AI as easy to use increases their purchase intentions. However, contrary to the literature (ElSayad & Mamdouh, 2024; Zhang et al., 2024), trust in AI has no direct significant effect on purchase intention.

Mediation analyses showed that both psychological ownership and perceived ease of use played significant mediating roles in the effects of utilitarian values and perceived information value on trust and purchase intention. These findings confirm that organismic elements play a critical role in transforming external stimuli into behavioral outcomes in the context of the S-O-R model (Cheng et al., 2017; Eroglu et al., 2003; Mehrabian & Russell, 1974).

Another remarkable finding of the study is that perceived AI intelligence plays a moderating role in these relationships. Specifically, perceiving the chatbot as very intelligent weakens the effect of psychological ownership and ease of use on purchase intention. This finding is consistent with studies by Jin & Youn (2023) and Lopes et al. (2024). Consumers may perceive overly intelligent systems as a "loss of control," leading them to delegate decisions and potentially weakening their intuitive and emotional connections.

**Practical Implications**

This study provides various practical recommendations for businesses designing artificial intelligence-based systems. By incorporating features such as personalized interfaces and customizable avatars, chatbot systems can not only operate efficiently but also encourage psychological ownership, thereby increasing trust and purchase intent (Xu et al., 2024).

Emphasizing benefits such as convenience, choice flexibility, and information access facilitates system adoption (Panda & Kaur, 2023). Brand managers should prioritize intuitive and user-supportive designs, as overly "smart" systems may reduce user control. AI-powered chatbots should be viewed not only as sales tools but also as instruments for brand engagement. Moreover, since the impact of perceived intelligence may vary across demographics, different chatbot strategies should be developed for younger or more tech-savvy consumers.

**Limitations and Future Research**

This study offers valuable insights into AI-powered chatbots in sports e-commerce but has several limitations. First, its cross-sectional design limits causal inference; future research could use longitudinal or experimental methods. Second, relying on self-reported data can lead to bias; behavioral data or system records are recommended for verification. Third, the sample was limited to one sector and region, which may affect generalizability; further studies should explore diverse contexts. Additionally, the model focused on utilitarian and informational factors, leaving out emotional drivers such as enjoyment or anthropomorphism. Finally, perceived intelligence was treated as a single construct; future research could examine its multidimensional effects.

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