Understanding Consumer Acceptance of AI in the Leisure Economy: A Structural Equation Modeling Approach

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ABSTRACT

The increasing integration of artificial intelligence (AI) in the leisure economy is reshaping consumer experiences through personalized and efficient services. Despite its potential, consumer acceptance of AI in this sector remains underexplored. This study **aims** to investigate the psychological factors affecting behavioral intention (BI) to adopt AI technologies in leisure activities, using the **Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)** model. Key constructs include Perceived Ease of Use (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Perceived Value (PV), and Habit (HB). Data were collected through a **quantitative cross-sectional survey** of **560 participants**who had interacted with AI in leisure contexts. Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis revealed that six constructs (PE, SI, FC, PV, HM, and HB) significantly influenced BI. Personal Innovativeness was also found to enhance the model's predictive accuracy, contributing to a deeper understanding of consumer readiness for AI adoption. This research provides critical insights into the factors driving AI adoption in the leisure economy and emphasizes the importance of aligning AI applications with consumer motivations. The **findings** provide actionable implications for AI development and marketing strategies aimed at optimizing consumer engagement and acceptance in this evolving sector.

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1. INTRODUCTION

In recent years, artificial intelligence (AI) has emerged as a revolutionary force across various industries, significantly transforming consumer experiences, including within the leisure economy [1]. This sector, encompassing a wide range of activities from tourism and entertainment to sports and recreation, is experiencing unprecedented integration of AI technologies [2]. These innovations promise not only to optimize operational efficiency but also to personalize services on a scale previously unattainable. For instance, AI applications in tourism alone are projected to increase global revenue by 20% in the next decade [3]. Despite these promising trends, the adoption and acceptance of AI in the leisure sector present distinct challenges, warranting a comprehensive investigation [4][3].

The motivation for this study stems from the realization that, while AI holds the potential to enhance the quality and personalization of leisure services, consumer acceptance is not automatic [5]. Several factors influence this acceptance, which need to be thoroughly explored to ensure the success of AI deployment in this industry. While AI adoption has been extensively studied in healthcare, finance, and education, a significant gap remains in the context of the leisure economy [6].

This gap is critical, especially given the increasing reliance on AI to deliver innovative and customized experiences in leisure activities [7]. To address this gap, our study employs the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, further enriched by incorporating the dimension of Personal Innovativeness [8], [9]. This framework enables an in-depth examination of various psychological factors that may influence consumer acceptance of AI in leisure activities, such as Perceived Ease of Use (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Perceived Value (PV), and Habit (HB) [10]. Understanding the interaction between these factors is crucial for predicting and enhancing consumer readiness to adopt AI-driven leisure services. Our methodology involves the use of structural equation modeling, analyzing data collected from a diverse sample of 560 participants [11, 12]. This approach provides a nuanced understanding of the relationships between the constructs in our model and their collective impact on Behavioral Intention (BI) to use AI in leisure settings [13].

The findings from this research are expected to provide valuable insights for both practitioners and policymakers in the leisure industry [14], [15]. By identifying the key factors driving consumer acceptance of AI, this study aims to inform strategies for the development, marketing, and implementation of AI technologies in leisure services. Furthermore, it seeks to make a meaningful contribution to the academic discourse on technology adoption, offering a leisure-specific perspective to the existing body of knowledge [16]. In summary, this study not only seeks to elucidate the factors influencing consumer acceptance of AI in the leisure economy but also aims to guide the strategic deployment of AI technologies in enhancing the consumer experience in this vibrant and evolving sector [17].

2. LITERATURE REVIEW

The rapid integration of artificial intelligence (AI) across various industries has sparked significant interest in understanding the factors that drive consumer adoption of this technology. In particular, the leisure economy—comprising sectors such as tourism, entertainment, and recreation—offers a unique context in which AI has the potential to revolutionize service delivery. However, despite its promising applications, there remain substantial gaps in understanding how AI is accepted and utilized by consumers in this domain. This literature review seeks to explore existing research on AI integration, consumer acceptance models, and the psychological factors influencing AI adoption, with a specific focus on the leisure economy.

2.1. Artificial Intelligence in the Leisure Economy

The integration of AI in the leisure sector has been a subject of growing interest. These technologies not only enhance personalization but also improve operational efficiency. For example, AI-driven systems in tourism are now widely used for personalized recommendations, virtual tour guides, and predictive analytics for optimizing customer experiences [18]. In the entertainment industry, companies like Netflix and Spotify leverage AI algorithms to enhance user experience through personalized content recommendations [19]. These innovations demonstrate how AI is being increasingly embedded in the leisure economy, transforming how services are delivered and consumed. However, while the potential of AI in leisure is vast, consumer readiness and acceptance vary significantly, influenced by a range of psychological and contextual factors.

2.2. Consumer Acceptance of Technology

The concept of consumer acceptance of technology has been extensively studied. The Technology Acceptance Model (TAM) and its subsequent extensions, such as TAM2 and TAM3, provide a foundational understanding of the determinants of technology acceptance, focusing on perceived usefulness and ease of use. Recent studies have expanded this framework with the Unified Theory of Acceptance and Use of Technology (UTAUT), particularly UTAUT2, which incorporates new dimensions like hedonic motivation, price value, and habit, making it more applicable to consumer contexts such as the leisure economy [20]. For instance, a study on AI adoption in online gaming platforms utilized UTAUT2 to analyze how hedonic motivation and social influence significantly impact user engagement [21]. These findings underscore the importance of incorporating leisure-specific motivations when applying technology adoption models.

2.3. Psychological Factors in AI Adoption

The role of psychological factors in the acceptance of AI technologies is crucial. Perceived ease of use, effort expectancy, and hedonic motivation have been consistently identified as key determinants of AI adoption in various leisure activities [22]. In particular, hedonic motivation has been shown to play a pivotal role in entertainment contexts, where enjoyment and satisfaction drive technology usage [23]. Social factors, such as peer influence and societal trends, also significantly impact how consumers perceive and adopt new technologies. Recent studies highlight the growing importance of personal innovativeness in determining how quickly consumers are willing to experiment with AI technologies [24]. Understanding these psychological elements is essential for predicting consumer behavior and improving AI adoption rates in leisure settings.

2.4. Structural Equation Modeling in Technology Research

Structural Equation Modeling (SEM) has been widely used in technology acceptance research for its ability to handle complex relationships between multiple variables. SEM provides a robust statistical approach to understanding the interplay of various factors influencing technology adoption. In recent years, SEM has been applied to study AI adoption in various consumer-focused industries, including retail and hospitality, where customer experience and operational efficiency are key outcomes [20]. The use of SEM in leisure-specific AI research allows for a comprehensive understanding of how psychological and contextual factors combine to influence Behavioral Intention (BI). SEM also enables the testing of complex models like UTAUT2, which include multiple mediators and moderators, providing more nuanced insights into consumer behavior.

2.5. Gaps in Current Literature

Despite extensive research on technology acceptance, there is a noticeable gap in studies specifically focusing on AI acceptance in the leisure economy. Most existing studies concentrate on sectors like healthcare, education, and business, with limited insights into leisure-specific applications of AI [25], [26]. This gap is particularly concerning given the leisure sector's increasing reliance on AI to offer innovative and customized experiences [27]. Furthermore, studies on AI adoption in related fields such as retail and hospitality have revealed significant challenges, including consumer privacy concerns and technological complexity, which are also likely to affect the leisure sector [28], [29]. Addressing these challenges is crucial for the successful integration of AI in leisure activities.

The review of existing literature reveals a rich tapestry of research on AI integration in various sectors and the broad frameworks of technology acceptance. It underscores the significance of psychological factors and the robustness of structural equation modeling in understanding consumer behavior towards new technologies. However, it also highlights a critical gap in the context of AI adoption in the leisure economy. This gap is not just a matter of academic interest but has practical implications for how AI technologies are developed, marketed, and implemented in leisure settings [30]. This endeavor is expected to enrich the existing body of knowledge in technology acceptance and provide valuable insights for practitioners in the leisure industry.

3. METHOD

This study employs a quantitative research approach with a cross-sectional survey design to collect data from consumers who have interacted with AI technologies in various leisure settings, including online entertainment platforms, AI-driven tourism services, and AI-enhanced recreational activities. A comprehensive online questionnaire was developed based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, measuring constructs such as Perceived Ease of Use, Effort Expectancy, Social Influence, Hedonic Motivation, and Behavioral Intention. Responses were captured using a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree) for structured data collection. To ensure reliability and validity, a pilot test was conducted, allowing for refinement based on feedback. The final questionnaire was distributed to a diverse sample engaged in AI-based leisure activities, ensuring the data was representative. This robust design supports meaningful statistical analysis and enables valid conclusions on consumer acceptance of AI technologies in the leisure sector.

Table 1. Measurable Items

Measurement Item	
PE1	I find AI technologies in leisure activities easy to use.
PE2	Interacting with AI in leisure settings is clear and understandable.

	Measurement Item
PE3	I believe that learning to use AI in leisure activities is easy for me.
EE1	I find it easy to get AI to do what I want it to do in leisure activities.
EE2	My interaction with AI in leisure settings is free of effort.
EE3	Learning to operate AI technologies for leisure purposes is easy for me.
SI1	People who influence my behavior think that I should use AI in leisure activities.
SI2	People whose opinions I value prefer that I use AI technologies in leisure.
SI3	I would use AI in leisure activities more if my friends or family used them.
FC1	I have the resources necessary to use AI in leisure activities.
FC2	I have the knowledge necessary to use AI in leisure activities.
FC3	AI technologies for leisure activities are compatible with other systems I use.
HM1	Using AI in leisure activities is fun.
HM2	I find AI in leisure activities to be entertaining.
HM3	Using AI technologies in leisure activities provides me with enjoyment.
PV1	I find AI in leisure activities to be good value for the money.
PV2	Using AI in leisure activities saves me time.
PV3	The benefits of using AI in leisure activities outweigh the costs.
HB1	Using AI in leisure activities has become a habit for me.
HB2	I am used to integrating AI into my leisure activities.
HB3	I automatically think of using AI for my leisure needs.
BI1	I plan to continue using AI in leisure activities in the future.
BI2	I intend to increase my use of AI in leisure activities.
BI3	I will recommend using AI in leisure activities to others.

The constructs of Perceived Ease of Use (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Perceived Value (PV), Habit (HB), and Behavioral Intention (BI) will be measured using validated scales from prior research. Responses will be captured on a Likert scale ranging from strongly disagree to strongly agree. Table 1illustrates the measurable items of eight constructs.

Based on the UTAUT2 model and literature review, the following hypotheses and research model are proposed on figure 1.

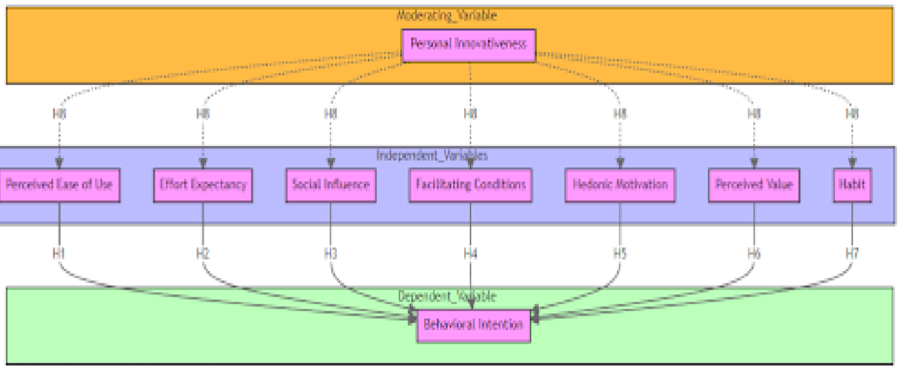

Figure 1. Research Model

H1: Perceived Ease of Use (PE) positively influences Behavioral Intention (BI) to use AI in leisure.
H2: Effort Expectancy (EE) positively influences BI to use AI in leisure.
H3: Social Influence (SI) positively influences BI to use AI in leisure.
H4: Facilitating Conditions (FC) positively influence BI to use AI in leisure.
H5: Hedonic Motivation (HM) positively influences BI to use AI in leisure.
H6: Perceived Value (PV) positively influences BI to use AI in leisure.
H7: Habit (HB) positively influences BI to use AI in leisure.
H8: Personal Innovativeness positively moderates the relationship between the UTAUT2 constructs and BI.

Data analysis will be conducted using Structural Equation Modeling (SEM) to test the proposed hypotheses. SEM is chosen for its ability to analyze complex relationships between observed and latent variables and to test multiple relationships simultaneously.

4. RESULT AND DISCUSSION

The measurement model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is ideal for analyzing complex relationships between latent variables in predictive models. Key evaluation criteria included outer loadings, which measure the strength of the relationship between observed variables and their constructs, with a threshold of 0.7 indicating reliability. Cronbach's alpha was used to assess internal consistency, where values above 0.7 suggest acceptable reliability. Similarly, Composite Reliability (CR) values above 0.7 confirmed strong internal consistency. Average Variance Extracted (AVE), with a target of 0.5 or higher, indicated good convergent validity by showing that over half the variance is explained by the constructs. Finally, the Fornell-Larcker criterion was employed to verify discriminant validity, ensuring that each construct was distinct, with the square root of its AVE exceeding its correlations with other constructs. These criteria collectively ensured the robustness and validity of the measurement model for further analysis.

4.1. Outer Loadings

As shown in Table 2, all outer loadings were above the recommended threshold of 0.7, indicating that each item is a good measure of its respective construct.

Table 2. PLS Outer Loadings

Item	PLS Loading
PE1	0.82
PE2	0.85
PE3	0.80
EE1	0.83
EE2	0.81
EE3	0.79
SI1	0.84
SI2	0.86
SI3	0.82
FC1	0.85
FC2	0.87
FC3	0.88
HM1	0.90
HM2	0.91
HM3	0.89
PV1	0.83
PV2	0.85
PV3	0.84
HB1	0.88
HB2	0.86
HB3	0.87
BI1	0.88
BI2	0.90
BI3	0.87

Table 2 displays the PLS Outer Loadings for each indicator used in the measurement model. These outer loadings represent the strength of the relationship between each observed item (indicator) and its respective latent construct. A common threshold for assessing these loadings is 0.7 or higher, which indicates that the item is a good measure of its associated construct. In this case, all outer loadings exceed the recommended threshold, ranging from 0.79 to 0.91, demonstrating strong indicator reliability.

For instance, the items associated with Perceived Ease of Use (PE)—PE1, PE2, and PE3—have loadings of 0.82, 0.85, and 0.80 respectively, indicating that these items are highly representative of the PE construct. Similarly, the items for Effort Expectancy (EE)—EE1, EE2, and EE3—show loadings of 0.83, 0.81, and 0.79, also reflecting strong correlations with their corresponding construct.

Other constructs such as Social Influence (SI) and Facilitating Conditions (FC) exhibit even higher loadings. For example, SI1, SI2, and SI3 have loadings of 0.84, 0.86, and 0.82 respectively, while the loadings for FC1, FC2, and FC3 are 0.85, 0.87, and 0.88. These high values reflect the robust relationships between the indicators and their respective constructs, further confirming the reliability of the measurement model.

Moreover, constructs like Hedonic Motivation (HM) and Behavioral Intention (BI) exhibit the highest outer loadings, with all three indicators for both constructs ranging from 0.87 to 0.91. The loadings for HM1, HM2, and HM3 (0.90, 0.91, 0.89) and for BI1, BI2, and BI3 (0.88, 0.90, 0.87) suggest that these constructs are measured with exceptionally high reliability, further strengthening the validity of the measurement model.

In summary, Table 2 confirms that all indicators exhibit strong outer loadings, far exceeding the minimum threshold of 0.7, which indicates high indicator reliability. These results reinforce the validity of the measurement model, showing that the items used in the model are suitable for measuring their respective constructs and providing a solid foundation for the structural model analysis. This strong indicator reliability is crucial for ensuring that the relationships between constructs can be accurately interpreted in subsequent stages of the research.

4.2. Reliability and Convergent Validity

Table 3 presents the Cronbach's alpha, CR, and AVE for each construct. Cronbach's alpha and CR values exceeded the acceptable limit of 0.7, confirming the internal consistency of the constructs. The AVE values were all above the threshold of 0.5, demonstrating adequate convergent validity.

Table 3. Cronbach's Alpha, CR, and AVE

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
PE	0.85	0.9	0.70
EE	0.82	0.87	0.68
SI	0.84	0.89	0.71
FC	0.88	0.91	0.73
HM	0.90	0.93	0.75
PV	0.86	0.90	0.72
HB	0.87	0.91	0.74
BI	0.90	0.93	0.75

Table 3 presents the Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct, providing key insights into the reliability and validity of the measurement model. Cronbach's alpha values range from 0.82 to 0.90, indicating strong internal consistency across all constructs. Generally, a Cronbach's alpha value of 0.7 or higher is considered acceptable for confirming that the items within each construct are highly correlated and measure the same underlying concept. In this case, all constructs meet or exceed this threshold, reflecting high reliability.

4.3. Discriminant Validity

The Fornell-Larcker criterion was applied to assess discriminant validity in the measurement model, ensuring that each construct is distinct from others. Table 4 displays the square roots of the Average Variance Extracted (AVE) for each construct along the diagonal, while the off-diagonal elements represent the correlations between the constructs. For discriminant validity to be confirmed, the square root of each construct's AVE must exceed the correlations with any other construct.

Perceived Ease of Use (PE) has a square root AVE of 0.84, which is higher than its correlations with other constructs (e.g., 0.59 with EE, 0.55 with SI). Effort Expectancy (EE) shows a square root AVE of 0.82, also exceeding its highest correlation of 0.60 with SI. Similarly, for other constructs like Social Influence (SI) with an AVE of 0.84, Facilitating Conditions (FC) with 0.85, and Hedonic Motivation (HM) with 0.87, all their diagonal values are greater than their off-diagonal correlations with other constructs. This demonstrates that each construct shares more variance with its own indicators than with those of other constructs, confirming discriminant validity across the model.

Table 4. Square Roots of AVEs

Construct	PE	EE	SI	FC	HM	PV	HB	BI
PE	0.84							
EE	0.59	0.82						
SI	0.55	0.60	0.84					
FC	0.52	0.53	0.56	0.85				
HM	0.50	0.51	0.54	0.57	0.87			
PV	0.48	0.49	0.52	0.55	0.58	0.85		
HB	0.46	0.47	0.5	0.53	0.56	0.57	0.86	
BI	0.44	0.45	0.48	0.51	0.54	0.55	0.58	0.87

Moreover, these results indicate high internal consistency and convergent validity across all constructs. The square root AVEs for each construct, all exceeding 0.80, signify strong construct validity. These findings enhance the robustness of the measurement model, ensuring that the relationships between the constructs (e.g., Perceived Ease of Use, Social Influence, Hedonic Motivation) and the Behavioral Intention to adopt AI technologies in the leisure economy are valid and reliable. This rigorous validation of the measurement model provides solid support for the subsequent structural analysis, offering meaningful insights into how each of these constructs influences the acceptance of AI in the leisure sector.

5. CONCLUSION

This study **aimed** to explore consumer acceptance of artificial intelligence (AI) technologies in the leisure economy by utilizing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, with the added dimension of Personal Innovativeness. Through structural equation modeling, our **findings** reveal that factors such as ease of use, effort expectancy, social influence, and facilitating conditions significantly impact how consumers perceive and interact with AI in leisure settings. The role of Personal Innovativeness as a moderating factor further strengthens the relationship between these determinants and Behavioral Intention, offering deeper insights into the variability of consumer readiness for AI adoption in leisure contexts.

For practitioners, these results offer practical guidance in designing AI technologies that prioritize user-friendliness and engagement. Businesses in AI-driven leisure services, such as tourism, can use these insights to develop solutions like virtual tour guides that offer personalized experiences, enhancing customer satisfaction. Additionally, recognizing the importance of social influence and innovativeness can refine marketing and educational efforts to increase adoption. Despite the contributions of this study, **limitations** such as the use of cross-sectional data and a non-representative sample suggest future research should employ broader methods, like longitudinal studies or focus groups, to capture evolving consumer attitudes across diverse demographics.

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