SPORMETRE
The Journal of Physical Education and Sport Sciences
Beden Eğitimi ve Spor Bilimleri Dergisi

DOI: 10.33689/spormetre.1606845
Research article

Geliş Tarihi (Received): 24.12.2024 Kabul Tarihi (Accepted): 22.06.2025 Online Yayın Tarihi (Published):30.06.2025

INVESTIGATING THE FACTORS INFLUENCING ADOPTION INTENTIONS OF CHATGPT FOR SPORT EVENTS*

Metin Argan[1], Halime Dinç[2†]
[1]Eskişehir Technical University, Faculty of Sports Sciences, ESKİŞEHİR
[2]Afyon Kocatepe University, Faculty of Sport Sciences, AFYONKARAHİSAR

Abstract: The growing interest in artificial intelligence tools like ChatGPT has led to numerous studies examining its role in enhancing information access, decision-making, and task efficiency across various domains. This study investigates the key factors influencing the adoption of ChatGPT as a tool for engaging with and learning about sports events, which encompass diverse content, formats, and objectives. Specifically, the research explores the effects of perceived ease of use, perceived usefulness, attitude, and subjective norms on behavioral intention and word-of-mouth (WOM) as mechanisms for technology dissemination. Adopting a quantitative approach, the study employs survey research to test a conceptual framework linking these six variables. The findings reveal that perceived ease of use and perceived usefulness positively influence users' attitudes toward ChatGPT, which in turn shape their behavioral intention to use the technology for learning about sports events. Additionally, subjective norms significantly impact behavioral intention and directly contribute to word-of-mouth sharing. Behavioral intention further emerges as a crucial factor, strongly driving word-of-mouth recommendations. These results offer valuable insights for future research on ChatGPT, specifically within the context of sports events. Practical implications suggest that event organizers and technology developers should prioritize improving ChatGPT's usability and perceived benefits to enhance adoption and encourage positive dissemination through user recommendations.

Key Words: Sport events, technology acceptance model, theory of planned behaviour, word of mouth, ChatGPT

SPOR ETKİNLİKLERİ İÇİN CHATGPT KULLANIM NİYETLERİNİ ETKİLEYEN FAKTÖRLERİN İNCELENMESİ

Öz: Yapay zeka araçlarına, özellikle ChatGPT'ye yönelik artan ilgi, bilgiye erişimi kolaylaştırma, karar alma süreçlerini destekleme ve çeşitli alanlarda görev verimliliğini artırma bağlamında birçok araştırmayı beraberinde getirmiştir. Bu çalışma, ChatGPT'nin spor etkinlikleri hakkında bilgi edinme ve etkileşim sağlama aracı olarak benimsenmesini etkileyen temel faktörleri incelemektedir. Spor etkinlikleri, farklı içerikler, formatlar ve hedefleri kapsadığı için, bu bağlamda ChatGPT'nin benimsenme dinamiklerinin anlaşılması önemli bir araştırma alanı olarak öne çıkmaktadır. Araştırma, algılanan kullanım kolaylığı, algılanan fayda, tutum, öznel normlar, davranışsal niyet ve ağızdan ağıza iletişim (WOM) gibi değişkenlerin birbirleriyle ilişkisini inceleyen kavramsal bir çerçeveye dayanmaktadır. Çalışmada nicel bir yöntem benimsenmiş ve bu çerçeve, anket tekniği kullanılarak test edilmiştir. Elde edilen bulgular, algılanan kullanım kolaylığı ve algılanan faydanın, kullanıcıların ChatGPT'ye yönelik tutumlarını olumlu yönde etkilediğini ve bu tutumların, teknolojiyi spor etkinlikleri hakkında bilgi edinme amacıyla kullanma niyetlerini şekillendirdiğini ortaya koymaktadır. Ayrıca, öznel normların davranışsal niyet üzerinde anlamlı bir etkisi olduğu ve doğrudan ağızdan ağıza iletişim yoluyla yayılımı desteklediği görülmüştür. Bunun yanı sıra, davranışsal niyet, ağızdan ağıza önerileri güçlü bir şekilde yönlendiren kritik bir faktör olarak öne çıkmıştır. Bu bulgular, spor etkinlikleri bağlamında ChatGPT'nin benimsenmesine ilişkin gelecekteki çalışmalara değerli içgörüler sunmaktadır. Uygulamalı açıdan, etkinlik organizatörleri ve teknoloji geliştiricileri, ChatGPT'nin kullanım kolaylığını ve algılanan faydasını artırarak, kullanıcıların bu teknolojiyi benimsemelerini ve olumlu öneriler yoluyla yaygınlaştırmalarını teşvik etmelidir.

Anahtar Kelimeler: Spor etkinlikleri, teknoloji kabul modeli, planlı davranış teorisi, ağızdan ağıza iletişim, ChatGPT.

---

* *This study was presented as an oral presentation at the International Conference on Sport Management and Marketing (ICOSMM-24), held on 21st–22nd November 2024 in Helsinki, Finland.*

† *Corressponding Author: Halime Dinç, PhD. E-mail: halimedinc@yandex.com*

INTRODUCTION

The rise of ChatGPT represents one of the most significant milestones in artificial intelligence, capturing the attention of millions worldwide with its unmatched ability to process and generate human-like language. Beyond its widespread applications in education and tourism, ChatGPT is now being explored for its potential to transform user experiences in sports event engagement, offering new ways to access information and make decisions (Forbes, 2023; Strzelecki, 2023). This rapid adoption has highlighted ChatGPT's potential to transform various industries, including education, tourism, and events (Dinç et al., 2024; Strzelecki, 2023). ChatGPT's ability to generate functional, fluent, and high-quality responses to human inquiries (Zhou et al., 2024) has positioned it as a valuable tool for event participants and organizers, particularly in areas such as decision-making, content personalization, and information retrieval (Zhong et al., 2023). In the sports industry, AI tools like ChatGPT are increasingly recognized for their potential to enhance user experiences and facilitate event engagement (N3XT Sports, 2023). Despite its growing adoption in fields like education and tourism (Saif et al., 2023; Carvalho and Ivanov, 2024), limited research has focused on ChatGPT's application in sports event contexts, particularly in aiding users to navigate and participate in such events effectively.

The reception and assimilation of technology are intrinsically linked to the cultural framework of the consuming group, substantially influencing their comprehension, assimilation and ultimate success in adopting these innovations (Jolly, 2024). The adoption of ChatGPT and similar AI technologies is often explained through theoretical frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Theory of Planned Behavior (TPB) (Ajzen, 2002). These models have been widely used to analyze factors influencing the intention to adopt technological innovations, such as perceived ease of use, perceived usefulness, attitudes, and subjective norms (Ahadzadeh et al., 2024; Mohr and Kühl, 2021). Similarly, knowledge-sharing behaviors and social influences have emerged as critical mediators in AI adoption (Lu et al., 2009). However, limited studies have examined the combined integration of TAM, TPB (Koul and Eydgahi, 2017), and word-of-mouth (WOM) as a framework for understanding ChatGPT adoption, particularly within the sports industry. In response to the identified research gap, this study aims to examine the acceptance of Chat GPT in sports event planning through the integration of TAM, TPB, and WOM frameworks. The research seeks to understand the factors influencing user intentions to utilize ChatGPT for discovering and engaging with sports events. By investigating dimensions such as the perceived usefulness and ease of use of ChatGPT in accessing sports event-related information, as well as social and motivational influences on adoption, the study aims to shed light on the underlying mechanisms driving ChatGPT usage intentions. Furthermore, the research explores how these intentions contribute to WOM as a key factor in the dissemination of this technology within the sports event context.

University students represent a crucial demographic for exploring ChatGPT usage, as they frequently integrate technology into both their academic and recreational lives. Recent studies highlight that research on university students' attitudes toward ChatGPT is still in its early stages, particularly concerning its use for recreational and sports activities (Zhang et al., 2024). Addressing this gap, the current study investigates the factors influencing ChatGPT adoption for learning about and engaging with sports events. By employing an integrated model that combines TAM, TPB, and WOM, this research seeks to uncover the dimensions shaping user intentions and their subsequent impact on WOM as a mechanism for technology dissemination.

The findings of this study have significant theoretical and practical implications. Theoretically, it expands existing literature by integrating TAM, TPB, and WOM into a unified framework, applying it to the underexplored context of sports events. This comprehensive approach bridges existing gaps and offers a pioneering model for understanding ChatGPT adoption in this domain. Practically, the results will assist event organizers and technology developers in designing strategies to enhance ChatGPT's usability, user satisfaction, and dissemination through WOM (Lucey, 2023). These findings provide actionable insights for leveraging AI tools in sports event ecosystems and lay a foundation for future research into AI-driven engagement strategies.

LITERATURE REVIEW

ChatGPT and Sport Events

ChatGPT, a conversational user interface powered by advanced large language models (LLMs) such as Generative Pre-trained Transformer (GPT), represents a groundbreaking evolution in artificial intelligence (AI). Developed initially with GPT-3 and now leveraging more advanced iterations like GPT-4, ChatGPT is pre-trained on extensive datasets and fine-tuned using supervised and reinforcement learning methods (Skjuve et al., 2023). With the transition to GPT-4, ChatGPT demonstrates significant advancements in understanding, fluency, and contextual relevance, further establishing its role as a state-of-the-art conversational AI system (Bubeck et al., 2023). These enhancements allow the tool to perform diverse tasks, including answering questions, generating and improving text, and even producing code (Adiwardana et al., 2020; Roller et al., 2020). Its ability to deliver specific, contextually relevant responses across a wide array of topics distinguishes ChatGPT from earlier conversational interfaces (Skjuve et al., 2023).

The application of ChatGPT transcends basic conversational AI, offering profound implications for various domains. In the realm of online information retrieval, tools like ChatGPT have introduced a paradigm shift from keyword-based searches to dialogue-driven, conversational approaches. This evolution enables users to engage in natural language interactions, bypassing rigid syntax requirements typical of traditional search engines (Tibau et al., 2024). However, this flexibility introduces challenges in structuring effective prompts and validating AI-generated responses, requiring users to adapt to new strategies for obtaining reliable information (Kasneci et al., 2023; Tibau et al., 2024). Despite these challenges, conversational AI's iterative nature facilitates personalized and intuitive information-seeking experiences (Brown, 2020; Silver et al., 2016).

In the context of sports, ChatGPT serves as a versatile tool for accessing information and planning events, offering users the ability to efficiently explore both local and international activities with detailed insights into event schedules, trends, and participation requirements. For local events, ChatGPT provides quick access to essential details such as dates, times, and locations, enabling users to discover community activities like running events, cycling tours, or football tournaments, which foster social connections and highlight its value as a community resource (Ferine et al., 2024). On a global scale, ChatGPT could enhance accessibility to major events such as the Olympic Games, FIFA World Cup, and Wimbledon by delivering comprehensive information on schedules, participant details, and live broadcast options, empowering users to stay informed and engage actively.

Generative AI tools like ChatGPT are also reshaping how sports enthusiasts interact with information. The integration of conversational AI into daily routines allows users to move beyond static, pre-defined queries, facilitating a more dynamic exploration of sports activities. This approach not only democratizes access to sports-related information but also promotes user-generated content (UGC), enriching the knowledge base used to train LLMs for future improvements (Bubeck et al., 2023; Salah et al., 2024).

While ChatGPT's influence is evident across various sectors, including education, healthcare, and entertainment (Cascella et al., 2023; Dowling and Lucey, 2023; Zhang et al., 2023), its role in the sports domain exemplifies how conversational AI can transform traditional interactions. By simplifying access to sports event information and enabling personalized planning, ChatGPT could help individuals save time and access sports events more easily and effectively.

Integration of Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB) for ChatGPT Adoption

The Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) are widely recognized frameworks employed to examine technology adoption behaviors, particularly within emerging contexts such as the utilization of ChatGPT. TAM, initially developed by Davis (1985, 1989), emphasizes two primary constructs: perceived usefulness (PU) and perceived ease of use (PEU). PU denotes the extent to which an individual believes that using a system will enhance their performance, whereas PEU reflects the degree to which the system is perceived as straightforward and user-friendly (Davis & Venkatesh, 1996). These constructs directly influence attitude (AT), which subsequently shapes behavioral intention (BI) to adopt and utilize the technology (Davis, 1989). TAM posits that technologies perceived as both useful and easy to use are more likely to be adopted (Del Giudice et al., 2023; Sabah, 2016).

The Theory of Planned Behavior (TPB), introduced by Ajzen (1985, 1991), extends the Theory of Reasoned Action (TRA) by encompassing behaviors that are not entirely under an individual's volitional control. According to TPB, an individual's behavioral intention (BI) is influenced by three factors: attitude (AT) toward the behavior, subjective norms (SN), and perceived behavioral control (PBC). Attitude pertains to the individual's evaluation of the behavior (e.g., the perceived benefits of using ChatGPT for sports event planning), while subjective norms denote the influence of significant referents, such as peers or family, on their intention to adopt the technology (Ajzen, 1991). Perceived behavioral control encapsulates users' confidence in their ability to effectively use the technology, contingent on available resources and opportunities (Ajzen, 1991; Ajzen & Fishbein, 1980).

Previous research underscores the significance of integrating TAM and TPB to establish a more comprehensive framework for analyzing technology adoption (Argan et al., 2024; Bano & Siddiqui, 2024). This integration provides a robust theoretical foundation for the current study. The combined model synthesizes TAM's emphasis on cognitive constructs (PU and PEU) with TPB's focus on social and motivational determinants (SN and PBC). This framework posits that perceived ease of use and perceived usefulness influence users' attitudes toward the technology, while subjective norms and perceived behavioral control further impact their behavioral intentions to adopt it (Lu et al., 2009; Mathieson, 1991).

Existing literature highlights the application of TAM and TPB across diverse contexts, illustrating their utility in understanding technology adoption behaviors. For example, Koul and Eydgahi (2018) examined the adoption of autonomous vehicle technology, reporting that perceived usefulness and perceived ease of use positively influenced the intention to use such vehicles. This finding highlight TAM’s utility in understanding individual technology adoption behaviors. Similarly, Irawan et al. (2021) investigated the acceptance of e-sports platforms, identifying that factor such as perceived usefulness, perceived ease of use, and trust significantly influenced users' intentions to engage with these platforms. This research demonstrates the multidimensional analytical capacity of an integrated TAM-TPB framework. Moreover, Hidayat et al. (2021) analyzed the acceptance of e-toll card technology, concluding that while perceived usefulness strongly shaped attitudes toward adoption, perceived ease of use exerted a less pronounced effect on behavioral intentions. Collectively, these findings affirm the value of integrating TAM and TPB to elucidate the multifaceted factors influencing technology adoption.

In the context of sports event planning, TAM and TPB provide a solid theoretical basis for examining how individual perceptions, social influences, and control factors shape technology adoption. For instance, users who perceive ChatGPT as an accessible and effective tool for generating accurate sports schedules and recommendations are more likely to integrate it into their sports event planning processes. Additionally, subjective norms -such as endorsements from friends or sports communities- can significantly enhance behavioral intentions and facilitate word-of-mouth dissemination of the tool.

By refining TAM and TPB to align with advancements in AI technologies, this integrated model presents a robust approach to investigating user adoption of ChatGPT in sports event engagement. This model bridges the gap between individual cognitive evaluations and broader social influences, offering a comprehensive framework to examine the interplay of cognitive, social, and motivational factors in technology adoption, particularly within the rapidly evolving domain of AI-driven tools.

Word of Mouth (WOM)

Word of Mouth (WOM) is defined as the intercommunication behavior between consumers regarding a product, service, or brand (Kozinets et al., 2010). WOM typically relates to marketing activities that can enhance public awareness of products and services. It effectively drives sales because the information is exchanged between people who trust and know each other, leading to a stronger impact on purchasing decisions (Kozinets et al., 2010). WOM is not limited to direct interpersonal communication; it also encompasses electronic word of mouth (eWOM), such as online reviews, forums, and social media posts on platforms like Instagram and Facebook. This form of digital communication has become increasingly significant for spreading products and innovations, as eWOM is often perceived as more reliable than company-driven marketing materials (Ahmad et al., 2022; Rynarzewska, 2019).

WOM plays a particularly significant role in the diffusion and adoption of technological innovations. It helps reduce perceived risks associated with adopting new technologies by providing informal evaluations and experiences from other users (Nguyen and Chaudhuri, 2019). This is especially true in the context of AI tools and emerging technologies, where positive WOM encourages new adopters by alleviating uncertainty and increasing trust in the technology (Kim et al., 2018). For instance, AI-based tools benefit greatly from user satisfaction and shared experiences, which act as key drivers for global adoption and diffusion. Recent studies have demonstrated that user-generated recommendations and feedback accelerate the acceptance of technologies by creating a foundation of trust and reducing perceived complexity (Jo and Park, 2024).

Furthermore, WOM contributes to both dissemination and trust, which are essential for widespread adoption. Unlike traditional advertising, WOM leverages social influence and behavioral imitation to encourage technology adoption Ahmad et al., 2022; Kim et al., 2018). This process aligns with the notion that adoption is inherently a social mechanism, where trust, shared communication, and personal connections play central roles in shaping user behavior. By acting as a reflection of user satisfaction and a mechanism for spreading innovations through informal recommendations, WOM emerges as a powerful driver in both consumer decisions and technology diffusion (Rynarzewska, 2019; Nguyen and Chaudhuri, 2019).

Theoretical Model and Hypothesis Development

The Technology Acceptance Model (TAM) suggests that users are more likely to adopt a technology if it is perceived as both easy to use and beneficial, supporting the idea that perceived ease of use (PEU) positively influences perceived usefulness (PU) (Davis and Venkatesh, 1996). In the context of sports events, PU refers to the degree to which users believe the technology -such as ChatGPT- enhances their ability to efficiently discover, plan, and engage with sports-related activities. PEU, on the other hand, reflects users' perception of how easy it is to utilize ChatGPT for navigating sports events, accessing schedules, or obtaining tailored event recommendations.

The relationship between PEU and PU has been supported by recent studies across various domains. This interpretation is grounded in the Technology Acceptance Model (Davis, 1989), which posits that perceived usefulness and perceived ease of use are key determinants of technology adoption. For example, Li et al. (2024) demonstrated that perceived ease of use significantly and positively impacts perceived usefulness in AI-supported planning tasks. Similarly, previous studies (e.g., Argan et al., 2024; Ma et al., 2023) have reinforced this connection, emphasizing that user-friendly technologies tend to enhance perceived benefits. Based on TAM's underlying principles and the findings in the existing literature, we propose that the ease of using ChatGPT for sports event planning positively influences users' perceptions of its usefulness in streamlining their event-related activities.

H_1: Perceived ease of use (PEU) positively influences the perceived usefulness (PU)

Perceived usefulness (PU) from technology is related to behavioral intention (BI) and is viewed as a strong predictor of adoption (Davis et al., 1989). When a prospective user perceives high-level benefits from a new technology and low-level difficulty in using it, the likelihood of forming a strong behavioral intention to adopt is high (Davis and Venkatesh, 1996). The perceived usefulness of the relevant technology directly affects the intention to adopt and utilize it. Similarly, the perceived ease of using technology to seek information through ChatGPT is generally considered an important variable influencing behavioral intention to use it (Silva et al., 2024).

The influence of PU and PEU on behavioral intention toward new technologies has long been recognized. For example, additionally, Hu (2022) conducted a study on Taiwanese university students in the context of AI-supported smart learning environments and confirmed that both perceived ease of use and perceived usefulness directly impacted students' behavioural intention to use the smart learning environment. Similarly, recent research conducted by Ma et al. (2024) found that PEU has a positive and significant effect on BI. Building upon this foundation, the following hypotheses were developed.

H_2. Perceived usefulness (PU) positively influences behavioral Intention (BI)

H_3. Perceived ease of use (PEU) positively influences behavioral Intention (BI)

Attitude (AT) is a key determinant of behavioral intention, as outlined in the Theory of Planned Behavior (TPB). It refers to an individual’s positive or negative psychological evaluation of a specific object or behavior (Ajzen, 1991; Koverola et al., 2022). In the context of technology adoption, attitude plays a crucial role in shaping users’ behavioral intentions and decisions to adopt new technologies. Research consistently shows that a positive attitude toward technology significantly influences behavioral intention. For example, Zhang et al. (2024) found that attitudes toward ChatGPT are directly linked to behavioral intentions. Additionally, Choung et al. (2023) and Li (2023) highlighted that individuals with high performance expectations tend to exhibit stronger behavioral intentions toward AI technologies. Based on this evidence, we propose the following hypothesis:

H_4: Attitude (AT) positively influences behavioral intention (BI)

Subjective norm (SN) is another critical determinant of behavioral intention within TPB. SN refers to the perceived social pressure to engage or not engage in a specific behavior, reflecting the influence of important individuals or groups in one’s social environment (Ajzen and Fishbein, 1980). This construct incorporates elements such as social learning, facilitation, and imitation, all of which significantly affect behavioral intentions. Strzelecki (2023) emphasized that subjective norms arise from the expectations and opinions of influential individuals, strongly affecting decisions to adopt new technologies. Empirical studies further validate this relationship. For instance, Jo and Bang (2023) found that social influence positively impacts users’ intentions to adopt ChatGPT. Similarly, Budhathoki et al. (2024) demonstrated that subjective norms significantly influence adoption intentions across different cultural contexts, such as the United Kingdom and Nepal. Building on these insights, we propose:

H_5: Subjective norm (SN) positively influences behavioral intention (BI)

In addition to its effect on behavioral intention, subjective norm also plays a pivotal role in shaping word-of-mouth (WOM). WOM is a critical construct in the dissemination and adoption of technologies like ChatGPT and is often driven by user satisfaction and positive experiences (Jo and Park, 2024). SN captures the degree of social approval or disapproval regarding a behavior, which directly influences users’ willingness to share recommendations. Md Husin et al. (2016) and Aziz et al. (2020) confirmed a positive relationship between SN and WOM, highlighting that social influence can motivate individuals to recommend technologies to others. Based on these findings, the following hypothesis was developed:

H_6: Subjective norm (SN) positively influences word-of-mouth (WOM).

Finally, behavioral intention (BI) is expected to have a direct effect on word-of-mouth (WOM) and play a significant role in its formation Positive behavioral intentions, particularly those shaped by satisfactory user experiences, not only foster a willingness to recommend but also amplify the frequency and reach of WOM, as individuals actively share their insights and endorsements with others (Kim et al., 2018) WOM, in turn, functions as a vital mechanism for accelerating the dissemination of information and fostering widespread adoption, particularly in the context of AI technologies like ChatGPT (Jo and Park, 2024). Grounded in these theoretical and empirical foundations, we propose the following hypothesis:

H_7: Behavioral intention (BI) significantly and positively influences word-of-mouth (WOM).

The proposed model, which integrates the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and Word of Mouth (WOM), is presented in Figure 1.

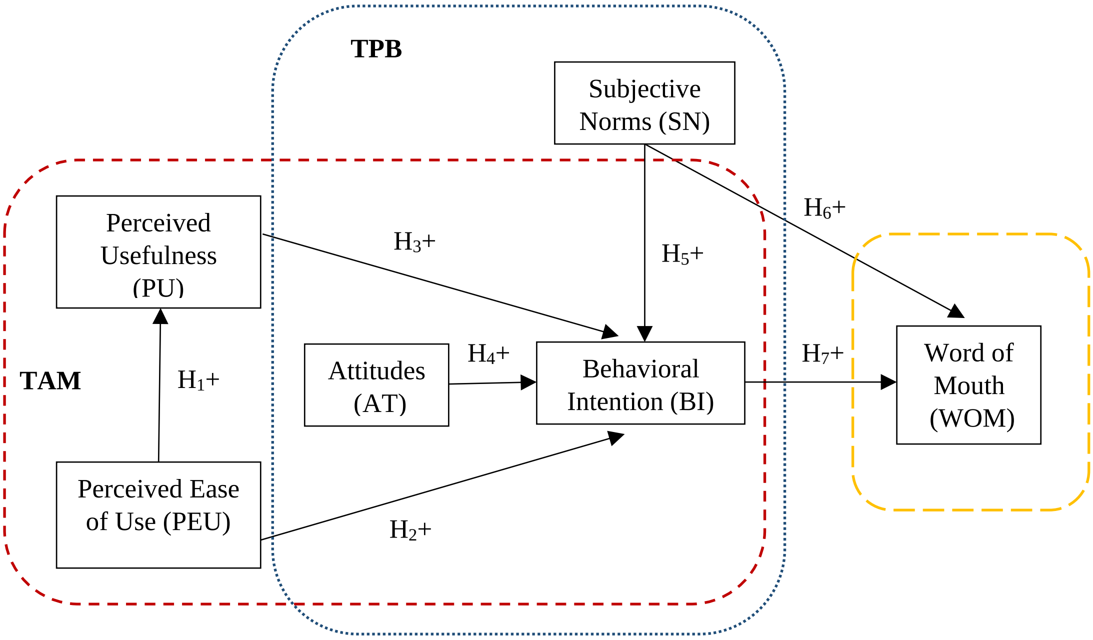


Figure 1. Proposed research model

METHODOLOGY

Sample and Data Collection

Research indicates that younger generations, particularly university students, are more inclined to adopt advanced artificial intelligence technologies like ChatGPT (Chan, 2023; Malynov and Prokhorov, 2023; Kobiella et al., 2024). University students, characterized by their technological literacy and accessibility, often utilize ChatGPT for various purposes, including language learning (Baskara, 2023), event selection (Malynov and Prokhorov, 2023), marketing tasks (Saputra et al., 2023), and academic assignments (Umirov, 2024). This makes them an ideal demographic for studies exploring ChatGPT usage.

For this study, data was collected from university students, who represent a significant social group actively participating in diverse activities, including sports events. These individuals use ChatGPT to make decisions, such as determining which sports events to attend. For example, as shown in a ChatGPT interaction (Figure 2), the tool can provide personalized suggestions for sports events, showcasing its usefulness in event planning. The research targeted 344 participants, a sample size deemed sufficient for a heterogeneous population distribution with a 95% confidence level (Hair et al., 2013). Data collection occurred between April and June 2024 through online surveys distributed via convenience sampling. The survey excluded incomplete or invalid responses, ensuring the integrity of the dataset.

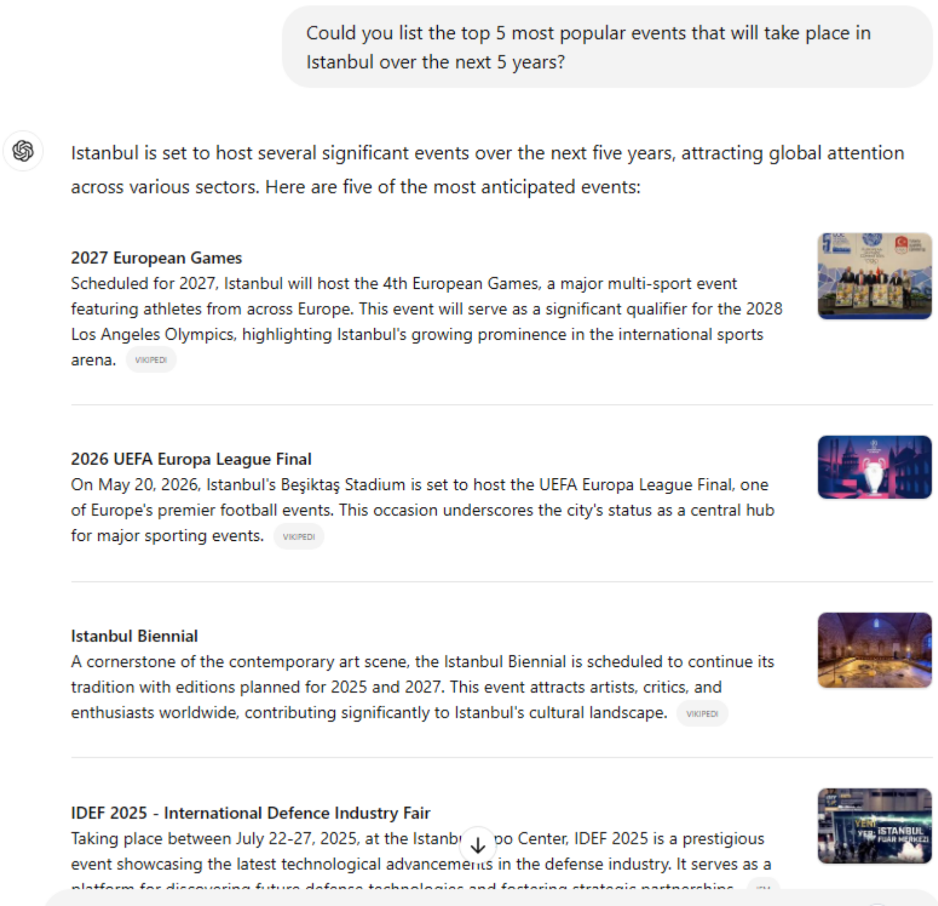


Figure 2. Example of ChatGPT providing sports event suggestions

Respondents were encouraged to share the online survey (Google docs) within their networks using the message, “Please share this survey with your environment for those who use ChatGPT for events,” thereby employing a snowball sampling technique to extend the reach of the survey and gather diverse responses (Goodman, 1961). This approach allowed the study to leverage existing social connections among users to identify additional participants, enhancing the sample size and diversity within the target demographic.

Measurement

In this study, scales previously validated and tested for reliability in relation to WOM were utilized, incorporating the constructs of the TAM and TPB models. These items assessed participants’ attitudes, behavioral intentions, subjective norms, and WOM in the context of using ChatGPT for sports events. Specific scales employed in the survey were adapted from established research. The three-item scale for perceived usefulness was based on the work of Lu et al. (2009). Measures for perceived ease of use and subjective norms were derived from Beh et al. (2021). The attitude scale, consisting of three items, was adapted from Abbas Naqvi et al. (2020), while the constructs for behavioral intention and WOM were modified from Zeithaml et al. (1996). To ensure relevance to the research context, additional questions were included to capture demographic variables participants’ age, gender, academic department, and level of education, as well as their use of ChatGPT for planning sports events. The questionnaire incorporated items measured on a 5-point Likert scale (ranging from 1 = strongly agree to 5 = strongly disagree).

Data Analyses

In the current study, IBM SPSS software was utilized for preliminary analyses and descriptive statistics. Additionally, the structural model was tested using Lisrel 8.80, a software tool designed for Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). Prior to conducting the CFA and SEM analyses, normality tests were performed, and common method bias (CMB) was assessed, as different scales were collected from the same sample within the same time frame. As recommended by Tabachnick and Fidell (2012), the dataset was evaluated for normality using statistical measures including skewness, kurtosis, and z-scores (<3.0) to detect outliers. Consistent with Cain et al. (2017), all scale items were assessed to ensure skewness values were below 3 and kurtosis values fell within the acceptable range of -2 to +2 before proceeding with the measurement model analysis. The skewness values ranged from -1.221 (lowest) to -0.33 (highest), and kurtosis values were between -0.016 (lowest) and 1.173 (highest), indicating that all items adhered to the normality thresholds. Construct reliability and validity were examined using Cronbach's alpha (α) and corrected item-total correlations. The reliability analysis confirmed that all variables demonstrated high internal consistency, and no items were excluded, as corrected item-total correlations verified the necessity of each item (Zijlmans et al., 2019). To account for potential common method bias (CMB), Harman's single-factor test was performed via exploratory factor analysis, where all items were loaded onto a single factor (Harman, 1976). The results indicated that the first factor explained 24.63% of the total variance, significantly below the threshold of 50%, thereby confirming the absence of substantial common method bias (Podsakoff et al., 2003). These findings underscore the reliability and validity of the data and support the robustness of the study's measures.

RESULTS

The characteristics of the study participants are listed in Table 1 below. The majority of participants are male (58.4%), In their fourth year of university (29.4%), between the ages of 21 and 22 (32.0%) and show an undergraduate degree (56.7%).

Table 1. *Demographic profile of participants (n= 344)*

		F	%
Age	18 to 20	90	26.2
	21 to 22	110	32.0
	23 to 24	74	21.5
	25 years and above	70	20.3
Gender	Female	143	41.6
	Male	241	58.4
Academic level	Vocational school	48	14.0
	High school	59	17.2
	Undergraduate	195	56.7
	Postgraduate	42	12.1
Degree	Prep school	33	9.6
	First year	39	11.3
	Second year	56	16.3
	Third year	62	18.0
	Forth year	101	29.4
	Fifth year and >	53	15.4

Evaluation of the Measurement Model

Prior to conducting confirmatory factor analysis (CFA), the means and standard deviations of the items across the six scales were analyzed. As shown in Table 2, the thresholds for all scales met the required standards. None of the scale items were excluded from the analysis, as all factor loadings exceeded the minimum threshold of 0.40. The fit indices [χ^2/df=1.62, RMSEA=0.043, SRMR=0.043, IFI=0.99, CFI=0.99, GFI=0.93, AGFI=0.90, NFI=0.99, NNFI=0.99] indicated a good model fit (Hair et al., 2006), validating the six-dimensional structure comprising perceived ease of use, perceived usefulness, attitude, subjective norms, behavioral intention, and word-of-mouth (WOM). To assess validity and reliability, Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) were calculated. Following established thresholds, a value of 0.7 or higher was considered acceptable for both Cronbach's alpha and CR, while an AVE value of 0.5 or higher was deemed satisfactory (Harrington, 2009; Brown, 2015). The results demonstrated that the study met all validity and reliability criteria, indicating that the measurement scales were both reliable and highly accurate.

Table 2. Findings of the measurement models

Constructs	*Items*	*Mean*	*Sd*	*λ*
Perceived Usefulness (PU)	PU1	4.06	1.05	0.83
	PU2	3.82	1.14	0.86
	PU3	4.08	1.01	0.91
Perceived Ease of Use (PEU)	PEU1	3.49	1.15	0.90
	PEU2	3.41	1.19	0.79
	PEU3	3.67	1.05	0.69
Attitude (AT)	AT1	4.08	1.00	0.86
	AT2	4.03	1.02	0.92
	AT3	3.99	1.03	0.92
	AT4	3.85	1.07	0.81
Behavioural Intention (BI)	INT1	4.01	1.02	0.80
	INT2	3.99	1.08	0.89
	INT3	4.01	1.03	0.92
Subjective Norms (SN)	SN1	4.01	1.04	0.86
	SN2	3.99	.99	0.89
	SN3	3.99	1.02	0.87
Word of Mouth (WOM)	WOM1	4.03	1.03	0.92
	WOM2	3.92	1.12	0.91
	WOM3	3.99	1.08	0.90

Note: λ: factor loading, Sd: standard deviation

Cronbach's alpha (α) values ranged between 0.85 and 0.94, and composite reliability (CR) scores were between 0.84 and 0.94, both exceeding the minimum required threshold of 0.70, as established by the validity and reliability assessment of the model (Hair et al., 2013). These results indicate that the items included in the study reliably quantify the intended constructs. Convergent validity was confirmed, with all item loadings ranging from 0.69 to 0.92, surpassing the acceptable threshold of 0.50. According to Hair et al. (2017), the average variance extracted (AVE) should exceed 0.50 to meet the validity criteria proposed by Fornell and Larcker (1981). Furthermore, the CR values were greater than the corresponding AVE values, as recommended by Fornell and Larcker (1981). The findings collectively suggest that the items sufficiently converge to measure the research variables effectively. Discriminant validity was also assessed by examining correlations between variables. The correlation coefficients were significant at a level less than 0.01, indicating no strong correlation or overlap between constructs. The results in Table 3 confirm that all values fall within the required threshold levels, illustrating the relationships between the constructs within the data collection instrument. For discriminant validity to be satisfied, the square roots of AVE must exceed the correlations between the related constructs. As shown in Table 3, the bolded diagonal values meet this requirement, as highlighted by Hulland (1999). These findings demonstrate that discriminant validity is not a concern in this study.

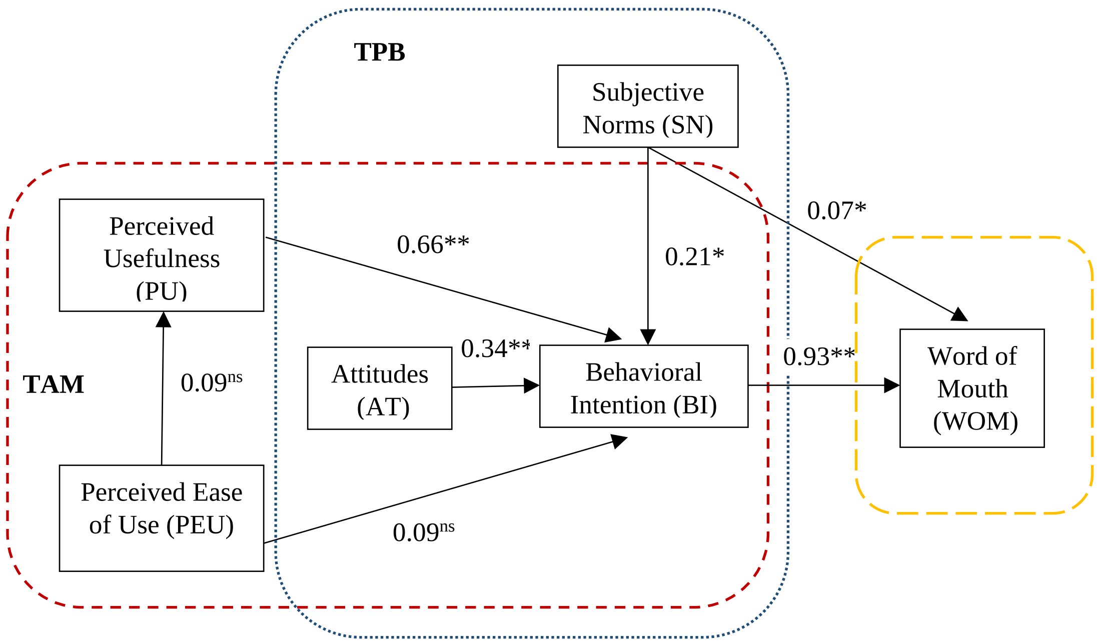
Table 3. *Findings descriptive statistics, reliability and discriminant validity*

Constructs	PU	PEU	AT	INT	SN	WOM
PU	0.86					
PEU	0.09	0.80				
AT	0.87**	0.05	0.88			
IN	0.83**	0.08	0.79**	0.87		
SN	0.80**	0.03	0.82**	0.76**	0.87	
WOM	0.83**	0.12*	0.80**	0.90**	0.77**	0.91
Alpha	0.89	0.85	0.93	0.91	0.90	0.94
CR	0.90	0.84	0.93	0.90	0.91	0.94
AVE	0.75	0.64	0.77	0.76	0.76	0.83
Mean	3.97	3.52	3.99	4.00	4.00	3.98
Standard Deviation	0.93	0.98	0.93	0.96	0.92	1.01

Notes: Correlations of variables (below the diagonal), the square roots of the AVE (diagonal), composite reliability (CR), and average variance extracted (AVE).
* p < 0.05; ** p < 0.0.1

Evaluation of the structural model

Lisrel software was employed to conduct the measurement model analysis. The results for the hypothetical model demonstrated a good level of fit. The goodness-of-fit indices for the proposed model were as follows: [χ^2/df = 3.16, RMSEA = 0.079, SRMR = 0.073, CFI = 0.97, GFI = 0.88, AGFI = 0.84, NFI = 0.97]. These values align well with the recommended thresholds for acceptable model fit, as outlined by Hair et al. (2017). The conceptual model is illustrated in Figure 3.



Notes: ns: not significant, * p < 0.05; ** p < 0.0.1

Figure 3. Results of the research model

The structural model provides an adequate fit to the data, and the hypotheses were evaluated based on the standardized coefficients (β) derived from the path analysis (Table 4). The findings reveal that perceived ease of use does not have a significant positive impact on perceived usefulness (β = 0.09, p > .05) or behavioral intention (β = 0.04, p > .05), resulting in the rejection of H_1 and H_2. However, perceived usefulness was found to have a positive and significant effect on behavioral intention (β = 0.66, p < .01), providing strong support for H_3. Furthermore, attitude (β = 0.34, p < .05) and subjective norms (β = 0.21, p < .05) were also found to positively influence behavioral intention, supporting H_4 and H_5. Subjective norms significantly impact word of mouth (WOM) (β = 0.07, T = 1.98, p < .05), supporting H_6. Similarly, behavioral intention (BI) has a very strong and significant influence on word of mouth (β = 0.93, T = 14.97, p < .01), providing support for H_7.

Table 4. Results of the Structural Model Hypotheses

Hypothesis	β	T values	*Results*
H1. Perceived Ease of Use (PEU) → Perceived Usefulness (PU)	0.09	1.47	*Rejected*
H2. Perceived Ease of Use (PEU) → Behavioural Intention (BI)	0.04	1.16	*Rejected*
H3. Perceived Usefulness (PU) → Behavioural Intention (BI)	0.66**	12.27	*Supported*
H4. Attitude (AT) → Behavioural Intention (BI)	0.34**	3.56	*Supported*
H5. Subjective Norms (SN) → Behavioural Intention (BI)	0.21*	2.19	*Supported*
H6. Subjective Norms (SN) → Word of Mouth (WOM)	0.07*	1.98	*Supported*
H7. Behavioural Intention (BI)→ Word of Mouth (WOM)	0.93**	14.97	*Supported*

* < 0.05; ** < 0.01

DISCUSSION AND CONCLUSION

The primary objective of this study was to evaluate the acceptance of ChatGPT technology within the event industry, with a particular emphasis on its application in sports event planning among Turkish university students—a demographic known for their high propensity to adopt new technologies. To the best of the authors' knowledge, this research represents one of the first attempts to explore the acceptance of ChatGPT in sports event planning by leveraging the integrated frameworks of TAM, TPB, and WOM. "The study's findings largely support the proposed comprehensive model through the application of confirmatory factor analysis (CFA) and structural equation modeling (SEM), highlighting the applicability of these theoretical approaches while acknowledging that not all hypotheses were confirmed."

Consistent with prior research on technology adoption and acceptance (e.g., Lu et al., 2009; Lucey, 2023), the results highlight the significant role of integrating multiple theoretical models to comprehensively understand user adoption behaviors. This study underscores the necessity of adopting a multidimensional perspective on technology acceptance, particularly in the context of recreational sports events. Such a perspective provides critical insights into how AI-powered tools like ChatGPT can enhance event planning and engagement, improve user satisfaction, and foster widespread dissemination through word-of-mouth communication.

The findings provide valuable insights into the factors influencing the adoption of ChatGPT for sports event planning. Perceived ease of use was not found to have a significant impact on either perceived usefulness or behavioral intention. While ease of use is often considered a foundational element of technology acceptance (Lu et al., 2009), its role may be less decisive in contexts where other factors, such as perceived benefits, dominate user decision-making. University students, the primary demographic in this study, are likely familiar with similar tools, which might reduce the importance of ease of use. They may already expect modern applications like ChatGPT to meet basic usability standards. In sports event planning, users might prioritize practical benefits, such as accessing information or making decisions efficiently, suggesting that perceived usefulness may hold greater weight than ease of use in this context.

On the other hand, perceived usefulness emerged as a critical determinant of behavioral intention, underscoring that users are more likely to adopt ChatGPT when they perceive it as an effective tool for planning and engaging with sports events. Previous research demonstrates how perceived usefulness significantly influences behavioral intention, particularly in contexts requiring efficiency and functionality, such as planning and engagement activities (Venkatesh and Davis, 2000; Gursoy et al., 2023). Attitude toward ChatGPT also emerged as a significant factor shaping behavioral intention, consistent with the Theory of Planned Behavior, which highlights the importance of attitudes in driving user intentions (Ajzen, 1991). Favorable perceptions of ChatGPT's capabilities encourage adoption, emphasizing the need to foster positive user experiences and highlight its utility (Ali et al., 2023). Subjective norms, reflecting the influence of social expectations, were found to positively affect both behavioral intention and word of mouth, aligning with prior research that emphasizes the role of peer influence in technology acceptance (Strzelecki, 2023). In the context of ChatGPT, users may perceive a sense of validation or pressure to conform to social trends, particularly when the technology is seen as innovative or widely endorsed. This combination of individual attitudes and social reinforcement suggests a meaningful motivational framework that can support adoption and promotion.

Behavioral intention was the strongest predictor of word-of-mouth communication, suggesting that individuals with a strong intention to adopt ChatGPT are likely to share their experiences and recommendations, further amplifying its adoption within their social circles (Lucey, 2023; Jo and Park, 2024). This aligns with previous studies showing that positive user experiences and behavioral intentions drive word-of-mouth dissemination in technology adoption (Podsakoff et al., 2003; Henseler et al., 2015). Social expectations and peer approval can create a sense of obligation or a desire to conform. If individuals perceive that their peers find ChatGPT valuable or are using it, they may feel motivated not only to adopt it themselves but also to share it with others to align with group norms (Masur et al., 2023).

Overall, the findings demonstrate that perceived usefulness, attitude, and subjective norms play significant roles in shaping behavioral intention and promoting word-of-mouth communication. These insights suggest that enhancing perceived usefulness, leveraging social influence, and fostering positive user attitudes are critical strategies.

Theoretical and practical implications

This study provides significant theoretical and practical contributions, particularly in understanding the adoption of ChatGPT in the context of sports events. On a theoretical level, it is one of the first to employ an integrative framework that combines the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Word-of-Mouth (WOM) models. This comprehensive approach bridges gaps in the existing literature by offering a holistic perspective on the mechanisms that influence user adoption and technology diffusion. Additionally, the research highlights the crucial role of subjective norms and behavioral intentions in driving WOM, offering valuable insights into how AI technologies like ChatGPT spread within specific user communities. By focusing on sports event planning, this study contributes to the limited body of knowledge regarding AI applications in leisure and recreation, affirming that perceived usefulness and positive attitudes are important for technology acceptance.

This study also provides practical implications for practitioners utilizing ChatGPT in the context of sports events and leisure. On a practical level, ChatGPT offers a wide range of benefits for both participants and organizers. Its ability to drive word-of-mouth (WOM) promotion is particularly noteworthy, as positive user experiences can encourage participants to share recommendations and attract broader audiences to future events. This organic dissemination of feedback amplifies the reach and impact of sports events, contributing to their long-term success. Furthermore, ChatGPT can provide multilingual support to facilitate ticket purchasing or reservation processes for participants from diverse linguistic backgrounds, thereby enhancing international accessibility. It can also deliver detailed information about competing athletes or teams, strengthening participant engagement with the event. For event organizers, ChatGPT serves as an effective tool for content creation, offering personalized event recommendations tailored to participants' interests and addressing specific inquiries to enhance the user-focused experience. Its capability to function as a virtual assistant during events allows it to respond promptly to participant needs, thereby improving overall satisfaction with the event.

Limitations and future studies

This study acknowledges certain limitations that open new avenues for future research, particularly in the context of sports events. First, the generalizability of the findings is limited due to the non-probability sampling method and the study’s focus on a single developing country, Turkey. Future research should replicate this study in similar cultural contexts and developed countries to achieve more universal insights. Such an approach would allow for broader comparisons and more generalizable outcomes, particularly in understanding the adoption of ChatGPT in different socio-economic settings.

Second, although this study included a relatively large sample of participants, the findings are influenced by the socio-cultural characteristics of Turkey. Future studies should consider cross-cultural research to capture more diverse perspectives on ChatGPT adoption for sports event planning. Such comparative research could uncover cultural differences and commonalities in how users perceive and utilize AI technologies like ChatGPT.

Third, this study primarily focused on university students in Turkey, a demographic that is technologically adept but not representative of the broader population attending sports events. Future research should expand its scope to include participants from a wider range of age groups as the adoption of ChatGPT and mobile applications becomes more prevalent. Examining varied demographics would provide richer insights into how different user groups interact with AI in the context of sports events.

Fourth, while this study focused on the antecedents of adoption intentions, future research should explore related factors such as perceived quality, satisfaction, and loyalty in using ChatGPT for sports events. These elements are critical for understanding long-term engagement and the sustainability of AI-driven technologies in the event industry. Furthermore, studies incorporating user feedback after ChatGPT experiences could help refine its features and improve its applicability in event-specific scenarios.

Fifth, this study investigated the use of ChatGPT in the general context of sports events. Future research should investigate the application of ChatGPT in distinct sports event scenarios, such as marathons, tournaments, or community-based sports activities. This focus would offer actionable insights into how AI technologies can be tailored to meet the unique demands of various event types, further enhancing their effectiveness and user satisfaction.

Finally, the finding that "Perceived Ease of Use" does not have a significant impact on Perceived Usefulness and Behavioral Intention suggests the need to test these relationships in groups with lower levels of technological proficiency or in regions with limited access to technology. Users' familiarity with technology may influence the effect of perceived ease of use, potentially altering its significance in these contexts. By addressing these limitations, future studies can build on the findings of this research and provide a deeper, more nuanced understanding of ChatGPT’s role in transforming the planning and execution of sports events.

REFERENCES

Adiwardana, D., Luong, M. T., So, D. R., Hall, J., Fiedel, N., Thoppilan, R., ... & Le, Q. V. (2020). Towards a human-like open-domain chatbot. *arXiv preprint arXiv:2001.09977*.

Ahadzadeh, A. S., Wu, S. L., & Sijia, X. (2024). Exploring academic intentions for ChatGPT: A perspective from the theory of planned behavior. *Chiang Mai University Journal of Agriculture and Science Research, 11*(2), e2024016. https://doi.org/10.12982/CMUJASR.2024.016

Ahmad, A., AlMallah, M. M., & AbedRabbo, M. (2022). Does eWOM influence entrepreneurial firms’ rate of diffusion of innovation? *Journal of Research in Marketing and Entrepreneurship, 24*(1), 92–111.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckmann (Eds.), *Action-control: From cognition to behavior* (pp. 11–39). Springer-Verlag.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. *Journal of Applied Social Psychology, 32*(4), 665–683. https://doi.org/10.1111/j.1559-1816.2002.tb00236.x

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Ali, F., Yasar, B., Ali, L., & Dogan, S. (2023). Antecedents and consequences of travelers' trust towards personalized travel recommendations offered by ChatGPT. *International Journal of Hospitality Management, 114*, 103588. https://doi.org/10.1016/j.ijhm.2023.103588

Argan, M., Gürbüz, B., Dursun, M. T., Dinç, H., & Tokay Argan, M. (2024). Usage intention of ChatGPT for health in Turkey: An extended technology acceptance model. *International Journal of Human–Computer Interaction*, 1–13.

Aziz, S., Afaq, Z., Muhammad, L., & Khan, B. (2020). The role of media, word of mouth, and subjective norms in determining attitude and intentions to purchase family takaful schemes. *Journal of Islamic Business and Management, 10*(1).

Bano, N., & Siddiqui, S. (2024). Consumers' intention towards the use of smart technologies in tourism and hospitality (T&H) industry: a deeper insight into the integration of TAM, TPB and trust. *Journal of Hospitality and Tourism Insights*, *7*(3), 1412-1434.

Baskara, R. (2023). Exploring the implications of ChatGPT for language learning in higher education. *Indonesian Journal of English Language Teaching and Applied Linguistics, 7*(2), 343–358.

Beh, P. K., Ganesan, Y., Iranmanesh, M., & Foroughi, B. (2021). Using smartwatches for fitness and health monitoring: The UTAUT2 combined with threat appraisal as moderators. *Behavior & Information Technology, 40*(3), 282–299.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., ... & Amodei, D. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems, 33*, 1877–1901.

Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., ... & Zhang, Y. (2023). Sparks of artificial general intelligence: Early experiments with GPT-4. *arXiv preprint arXiv:2303.12712*.

Budhathoki, T., Zirar, A., Njoya, E. T., & Timsina, A. (2024). ChatGPT adoption and anxiety: a cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT). *Studies in Higher Education*, 1–16. https://doi.org/10.1080/03075079.2024.2333937

Cain, M. K., Zhang, Z., & Yuan, K. H. (2017). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior Research Methods*, *49*, 1716–1735.

Carvalho, I., & Ivanov, S. (2024). ChatGPT for tourism: Applications, benefits, and risks. *Tourism Review, 79*(2), 290–303.

Cascella, M., Montomoli, J., Bellini, V., & Bignami, E. (2023). Evaluating the feasibility of ChatGPT in healthcare: An analysis of multiple clinical and research scenarios. *Journal of Medical Systems, 47*(1), 33.

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education, 20*(38), 1–25.

Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human–Computer Interaction, 39*(9), 1727–1739.

Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results (Doctoral dissertation). Massachusetts Institute of Technology.

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

Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: Three experiments. *International Journal of Human-Computer Studies, 45*(1), 19–45. https://doi.org/10.1006/ijhc.1996.0040

Del Giudice, M., Scuotto, V., & Maggioni, V. (2023). Factors influencing the adoption of artificial intelligence: An extended TAM perspective. *Technological Forecasting and Social Change, 191*, 122447. https://doi.org/10.1016/j.techfore.2023.122447

Dinç, T., et al. (2024). A comprehensive model of ChatGPT acceptance in events using technology acceptance model, theory of planned behavior, and word of mouth. *International Journal of Event and Festival Management*.

Dowling, M., & Lucey, B. (2023). ChatGPT for (finance) research: The Bananarama Conjecture. *Finance Research Letters, 53*, 103662.

Ferine, K. F., Nadriati, S., Arif, M., Muharmi, Y., & Kusuma, C. (2024). Socialization of the use of ChatGPT in increasing village community resources. *Journal of Human and Education (JAHE), 4*(3), 271–277.

Forbes. (2023). What is ChatGPT? A review of the AI in its own words. *Forbes*. Retrieved from https://www.forbes.com/advisor/business/software/what-is-chatgpt/ (accessed 15 December 2024).

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Goodman, L. A. (1961). Snowball sampling. *The Annals of Mathematical Statistics, 32*(1), 148–167. https://doi.org/10.1214/aoms/1177705148

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management, 49*, 157–169.

Hair, E., Halle, T., Terry-Humen, E., Lavelle, B., & Calkins, J. (2006). Children's school readiness in the ECLS-K: Predictions to academic, health, and social outcomes in first grade. *Early Childhood Research Quarterly, 21*(4), 431-454.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning, 46*(1–2), 1–12.

Hair, J., Hult, G., Ringle, C., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equations Modeling (PLS-SEM)*. Sage, Los Angeles.

Harman, H. H. (1976). *Modern factor analysis*. University of Chicago Press.

Harrington, D. (2009). *Confirmatory factor analysis*. Oxford University Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115–135.

Hidayat, R., Hidayat, R. A., Suswanto, B., & Tholib, A. (2021, October). Green Technology E-toll Card: Level of acceptance and use of a technology. In *2021 IEEE 7th Information Technology International Seminar (ITIS)* (pp. 1-6). IEEE.

Hu, Y. H. (2022). Effects and acceptance of precision education in an AI-supported smart learning environment. *Education and Information Technologies, 27*(2), 2013–2037.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal, 20*(2), 195–204.

Irawan, D. A., Adiputra, I., & Arshanty, R. P. (2021, August). E-Recruitment: Extending Technology Acceptance Model in the Indonesian Context. In *2021 International Conference on Information Management and Technology (ICIMTech)* (Vol. 1, pp. 99-104). IEEE.

Jo, H., & Bang, Y. (2023). Analyzing ChatGPT adoption drivers with the TOEK framework. *Scientific Reports, 13*(1), 22606.

Jo, H., & Park, D. H. (2024). Effects of ChatGPT's AI capabilities and human-like traits on spreading information in work environments. *Scientific Reports, 14*(1), 7806. https://doi.org/10.1038/s41598-024-57977-0

Jolly, C. (2024). Cross-cultural perspectives on digital media and well-being: A narrative review. *IAHRW International Journal of Social Sciences Review, 12*(1).

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274.

Kim, S., Kandampully, J., & Bilgihan, A. (2018). The influence of eWOM communications: An application of online social network framework. *Computers in Human Behavior, 80*, 243–254. https://doi.org/10.1016/j.chb.2017.11.015

Kobiella, C., Flores López, Y. S., Waltenberger, F., Draxler, F., & Schmidt, A. (2024). How the use of ChatGPT changes young professionals' perception of productivity and accomplishment. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–16.

Koul, S., & Eydgahi, A. (2017). A systematic review of technology adoption frameworks and their applications. *Journal of Technology Management & Innovation*, 12(4), 106–113.

Koul, S., & Eydgahi, A. (2018). Utilizing technology acceptance model (TAM) for driverless car technology adoption. *Journal of technology management & innovation*, *13*(4), 37-46.

Koverola, M., Kunnari, A., Sundvall, J., & Laakasuo, M. (2022). General attitudes towards robots scale (GAToRS): A new instrument for social surveys. *International Journal of Social Robotics*, 14(7), 1559–1581. https://doi.org/10.1007/s12369-022-00880-3

Kozinets, R. V., De Valck, K., Wojnicki, A. C., & Wilner, S. J. S. (2010). Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of Marketing*, 74(2), 71–89. https://doi.org/10.1509/jm.74.2.71

Li, S., Han, R., Fu, T., Chen, M., & Zhang, Y. (2024). Tourists' behavioural intentions to use ChatGPT for tour route planning: An extended TAM model including rational and emotional factors. *Current Issues in Tourism*, 1–17. https://doi.org/10.1080/13683500.2024.2355563

Lu, Y., Zhou, T., & Wang, B. (2009). Exploring Chinese users' acceptance of instant messaging using the theory of planned behavior, the technology acceptance model, and the flow theory. *Computers in Human Behavior*, 25(1), 29–39. https://doi.org/10.1016/j.chb.2008.06.002

Lucey, P. (2023). The future of sports coverage: Part 1. *Stats Perform*. Available at: https://www.statsperform.com/resource/stats-performs-chief-scientist-on-chatgpts-role-in-the-future-of-sports-coverage-part-1/ (accessed 15 December 2024).

Ma, J., Wang, P., Li, B., Wang, T., Pang, X. S., & Wang, D. (2024). Exploring user adoption of ChatGPT: A technology acceptance model perspective. *International Journal of Human–Computer Interaction*, 1–15. https://doi.org/10.1080/10447318.2024.2314358

Malynov, A., & Prokhorov, I. (2023). Enhancing event selection with ChatGPT-powered chatbot assistant: An innovative approach to input data preparation. In *Biologically Inspired Cognitive Architectures Meeting* (pp. 588–594). Cham: Springer Nature Switzerland.

Masur, P. K., Bazarova, N. N., & DiFranzo, D. (2023). The impact of what others do, approve of, and expect you to do: An in-depth analysis of social norms and self-disclosure on social media. *Social Media + Society*, 9(1), 20563051231156401.

Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Information Systems Research*, 2(3), 173–191. https://doi.org/10.1287/isre.2.3.173

Md Husin, M., Ismail, N., & Ab Rahman, A. (2016). The roles of mass media, word of mouth and subjective norm in family takaful purchase intention. *Journal of Islamic Marketing*, 7(1), 59–73. https://doi.org/10.1108/JIMA-03-2015-0020

Mohr, S., & Kühl, R. (2021). Acceptance of artificial intelligence in German agriculture: An application of the technology acceptance model and the theory of planned behavior. *Precision Agriculture*, 22(6), 1816–1844.

N3XT Sports. (2023). Understanding the first steps to AI adoption in sports. *N3XT Sports*. Available at: https://www.n3xtsports.com (accessed 15 December 2024).

Naqvi, A. M. H., Jiang, Y., Miao, M., & Naqvi, M. H. (2020). The effect of social influence, trust, and entertainment value on social media use: Evidence from Pakistan. *Cogent Business and Management*, 7(1), 1–23.

Nguyen, H. T., & Chaudhuri, M. (2019). Making new products go viral and succeed. *International Journal of Research in Marketing*, 36(1), 39–62. https://doi.org/10.1016/j.ijresmar.2018.09.007

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903.

Roller, S., Dinan, E., Goyal, N., Ju, D., Williamson, M., Liu, Y., ... & Smith, E. M. (2020). Recipes for building an open-domain chatbot. *arXiv preprint arXiv:2004.13637*.

Rynarzewska, A. I. (2019). It's not fake, it's biased: Insights into morality of incentivized reviewers. *Journal of Consumer Marketing*, 36(3), 401–409. https://doi.org/10.1108/JCM-02-2018-2570

Sabah, N. M. (2016). Exploring students' awareness and perceptions: Influencing factors and individual differences driving m-learning adoption. *Computers in Human Behavior*, 65, 522–533. https://doi.org/10.1016/j.chb.2016.09.009

Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfiai, M. M., & Arif, M. (2024). ChatGPT: Validating technology acceptance model (TAM) in education sector via ubiquitous learning mechanism. *Computers in Human Behavior*, 154, 108097. https://doi.org/10.1016/j.chb.2023.108097

Salah, M., Alhalbusi, H., Ismail, M. M., & Abdelfattah, F. (2024). Chatting with ChatGPT: Decoding the mind of chatbot users and unveiling the intricate connections between user perception, trust, and stereotype perception on self-esteem and psychological well-being. *Current Psychology*, 43(9), 7843–7858.

Saputra, R., Nasution, M. I. P., & Dharma, B. (2023). The impact of using AI ChatGPT on marketing effectiveness: A case study on Instagram marketing. *Indonesian Journal of Economics and Management*, 3(3), 603–617.

Silva, O., Nunes, J., & Sousa, Á. (2024). University students' perceptions of ChatGPT: Factors that affect their behavioural intention, usage and utility perceived. In *ICERI2024 Proceedings* (pp. 7427–7434). IATED.

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., Van Den Driessche, G., ... & Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, 529(7587), 484–489.

Skjuve, M., Følstad, A., & Brandtzaeg, P. B. (2023). The user experience of ChatGPT: Findings from a questionnaire study of early users. In *Proceedings of the 5th International Conference on Conversational User Interfaces* (pp. 1–10).

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, 1–14.

Tabachnick, B. G., & Fidell, L. S. (2012). *Using multivariate statistics* (6th ed.). Boston: Pearson.

Tibau, M., Siqueira, S. W. M., & Nunes, B. P. (2024). ChatGPT for chatting and searching: Repurposing search behavior. *Library & Information Science Research*, 46(4), 101331.

Umirov, S. (2024). Should we create better assignments instead of worrying about generative AI (such as ChatGPT)? *American Journal of Language, Literacy and Learning in STEM Education*, 2(1), 420–423.

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

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing*, 60(2), 31–46.

Zhong, Q., Ding, L., Liu, J., Du, B., & Tao, D. (2023). Can ChatGPT understand too? A comparative study on ChatGPT and fine-tuned BERT. *arXiv preprint arXiv:2302.10198*. https://doi.org/10.48550/arXiv.2302.10198

Zhou, C., Li, Q., Li, C., Yu, J., Liu, Y., Wang, G., ... & Sun, L. (2024). A comprehensive survey on pretrained foundation models: A history from BERT to ChatGPT. *International Journal of Machine Learning and Cybernetics*, 1–65.

Zijlmans, E., van der Ark, L. A., & Sijtsma, K. (2019). Item-score reliability as a selection tool in test construction. *Frontiers in Psychology*, 9, 2298.