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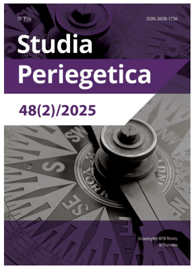

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The Sustainable Shift: Employees' Behavioural Intentions Towards the Use of Artificial Intelligence in Sustainable Tourism

Abstract. The study aimed to assess the effect of eight factors that shape employees' behavioural intentions regarding the use of AI systems in their professional environments: performance and effort expectancy, social influence, facilitating conditions, relative advantage, compatibility, complexity and trialability. These factors were used as predictors of behavioural intention and use behaviour. Data for PLS-SEM analysis were collected from tourism employees using an online survey. Findings revealed a positive and substantial correlation between factors like performance expectancy, effort expectancy and social influence on the one hand and behavioural intentions on the other. In addition, facilitating conditions, compatibility, complexity and trialability were found to be positively and significantly correlated with behavioural intentions, which were also correlated with employees' use of AI. The study contributes to a more nuanced understanding of the human dimension in the implementation of AI, offering insights for organisations seeking to navigate the complex behavioural landscape of technological change.

Keywords: artificial intelligence, diffusion of innovation theory, sustainable tourism, unified theory of acceptance and use of technology

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1. Introduction

The nexus between artificial intelligence (AI) and tourism has gained recognition from scholars in the fields of tourism and hospitality (Suanpang & Pothipassa, 2024; Tong et al., 2022).The use of AI technologies has been studied in numerous fields such as employee behaviour in organisations (Ramachandran et al., 2021) in the transport industry (Klumpp & Zijm, 2019), food sector (Ramirez-Asis et al., 2021) and the financial sector (Königstorfer & Thalmann, 2020). Applications of AI in the tourism sector range from personalised recommendations, smart infrastructure, to predictive analytics, all aimed at enhancing traveller experiences (Aliyah et al., 2023). The emergence of these applications is prompting businesses to adopt more advanced technological systems, in an effort to offer improved products and services while increasing productivity and gaining a competitive advantage (Veluru, 2023).

According to Sarker (2021), AI is employed by numerous sectors to enhance business processes, reduce costs, optimise client satisfaction, and extend operational capacity. Dash et al. (2019) note that the use of AI technologies within the business environment is not an overnight phenomenon but rather a progressive development, as AI technologies offer significant benefits over the human workforce. This trend is facilitated by continuous AI improvements and the growing pace of integration of AI with service delivery systems within organisations (Gursoy et al., 2019; Helo & Hao, 2021). The adoption of AI by businesses and industries has the potential to revolutionise the manner in which organisations and societies discover, learn, live, communicate, and work (Singh et al., 2023). AI systems have been utilised to enhance skills in data collection, marketing, advertising, business operations, and personal assistance (Mashapa & Atanga, 2023). As AI technologies continue to evolve, their adoption will likely expand across various sectors, particularly within tourism establishments. According to Kazak et al. (2020), AI tools can surpass old search engines and also reduce labour requirements in the tourism industry.

This study aims to fill knowledge gaps regarding employees' behavioural intentions to use AI in order to promoting sustainable tourism practices. Despite the growing importance of sustainability in tourism, there is still little research that links employee perspectives and the role of AI in enhancing sustainable practices, particularly in Southern Africa (Tong et al., 2022; Veluru, 2023). As these regions often grapple with insufficient infrastructure development and a limited focus on sustainability, there is an urgent need for insights from the workforce directly involved in tourism operations. This study therefore tries to address the pressing issues of environmental conservation and responsible tourism in areas where these topics are still developing (Mashapa & Dube, 2023; Ngepah et al., 2021). By focusing on employee intentions and attitudes towards AI, the authors seek to identify potential barriers and motivators that could shape the integration of AI in sustainable practices. Such information is vital for policymakers and tourism stakeholders looking to foster an environmentally responsible industry. In contrast to existing studies, which often examine broader technological impacts on tourism or investigate sustainability in isolation, the following study specifically focuses on the intersection of employee behaviour and AI implementation in the context of sustainable tourism. It aims to provide a nuanced understanding of how local employees perceive and adapt to technological advancements that could enhance sustainability efforts, thus contributing a fresh perspective to the ongoing discourse on sustainable tourism development.

2. Literature Review

2.1. The Concept of Artificial Intelligence

AI is an umbrella term that encompasses various technological fields such as cognitive computing, deep learning, neural networks, computer vision, natural language processing, and machine learning (Kashem et al., 2022; Ruël & Njoku, 2020). According to Welukar and Bajoria (2021), AI refers to programmes, algorithms, systems, or machines that exhibit intelligence. Machine learning (ML) is a subset of AI that employs concepts and resources from other fields, particularly programming, to create systems that automatically recognise meaningful patterns in data, a subject closely associated with data mining (Christopoulou, 2024). In fact, the category of ML covers the vast majority of AI developments and applications (García-Madurga & Grilló-Méndez, 2023). In the tourism sector, ML can be leveraged to generate data that can be used by employees to produce improved responses to shifts in market conditions and consumer demands. AI encompasses a wide range of technological features and services, including big data, chatbots, virtual reality (VR), multi-agent systems, robotic machines, distributed agent systems, 3D modelling, and virtual personal assistants (Maziriri et al., 2023). The term AI can also be used to refer to systems that mimic human cognitive processes, such as learning, reasoning, and problem-solving (Rong et al., 2020). In essence, AI is a collective term for intelligent machines capable of replicating human intelligence to devise problem-solving strategies in complex situations.

2.2. Sustainable Tourism

According to Suanpang and Pothipassa (2024), sustainable tourism is frequently linked to economic development and job opportunities, which should be considered not only within the travel sector but also across the multifaceted and far-reaching tourism value chain. Additionally, Begum et al. (2014) note that the participation of all stakeholders is crucial for the sustainability of tourism activities. Sustainability in tourism involves operations and capacity-building initiatives that promote awareness of environmental issues, conserve and protect the planet, value biodiversity, and enhance the overall health and employment of local communities by supporting the local economy as well as both humans and nature (Baloch et al., 2022). In summary, sustainable tourism aims to alleviate poverty by generating employment and creating sustainable workplaces.

In addition to its potential for job creation, tourism is anticipated to contribute to more balanced regional development by disseminating the benefits of economic activity, capital, and resources across sectors through the development of value chains, and by assisting in the conservation and sharing of cultural heritage (Rodiris, 2021). The objective of balanced regional development in sustainable tourism can be achieved through the utilisation of sustainable development goals (SDGs) and stakeholder participation. Sustainable tourism is characterised by efforts to reduce poverty, develop rural areas, promote equality, preserve culture, protect the planet, mitigate climate change, and support the SDGs (Liu, 2003). The adoption of policies promoted by the United Nations World Tourism Organization (UNWTO) enables tourism organisations to practise sustainable tourism through job creation, the implementation of sound environmental practices, and poverty reduction in communities while generating profits.

The tourism industry has the potential to lead the transition toward a new green economy (Juvan et al., 2023; Mashapa et al., 2019), thereby fostering greater support and policy development for achieving sustainability. From the standpoint of balanced and equitable development, sustainable tourism thrives in a green economy by prioritizing productivity enhancement, embracing innovative and eco-friendly production methods, shifting towards a circular economy, and replacing unsustainable jobs with green employment opportunities (Štreimikienė et al., 2020). However, the swift growth of the green economy may necessitate additional training for personnel, potentially leaving some inexperienced individuals to engage in practices for which they are not adequately prepared (Ram et al., 2019).

This study is closely linked to Sustainable Development Goal (SDG) 8, which focuses on decent work and economic growth. This SDG aims to promote sustained, inclusive, and sustainable economic growth, along with full and productive employment and decent work for all. This is aligned with the findings of a study by Parisotto (2015), who emphasises that employees' behavioural intentions regarding the use of AI in sustainable tourism are closely related to the impact of new technologies, such as AI, on employment, efficiency, and the nature of work within the tourism sector. This, in turn, can lead to more decent and sustainable job opportunities. Furthermore, this study is closely aligned with SDG 12, which focuses on responsible consumption and production, especially in the area of tourism, as stipulated by Target 12.A: Develop and implement tools to monitor sustainable tourism (Arora and Mishra, 2023). In addition, Lakhouit (2025) highlights that AI can enhance resource management, improve waste management, and encourage sustainable practices among both businesses and tourists. Therefore, the behavioural intentions of employees play a crucial role in the effective implementation of these AI-driven sustainable initiatives. By enhancing resource management and promoting more sustainable behaviours, AI can significantly influence both business operations and tourist activities (Liberato et al., 2024).

Finally, this study is consistent with SDG 17: Partnerships for the Goals, by emphasising that the integration of AI in sustainable tourism necessitates collaboration among various stakeholders, including businesses, employees, technology providers, and policymakers. The role that AI can play in fostering such multi-stakeholder partnerships is discussed by Bang-Ning et al. (2025).

3. Theoretical Underpinning and Hypothesis Development

The Unified Theory of Acceptance and Use of Technology (UTAUT) and the Diffusion of Innovation Theory (DIT) serve as the theoretical foundations for this study. Venkatesh et al. (2003) developed the UTAUT as a cohesive framework that integrates different perspectives on product and consumer acceptability (Williams et al., 2015). The UTAUT concept has proven effective (Dwivedi et al., 2017) in explaining how individuals adopt new technologies by emphasising the continuous search for new technologies that could be used by different organisations to enhance their goods and services.

The degree to which employees of tourism organisations are willing to adopt AI tools depends on geographic locations and cultural norms, particularly in conglomerate businesses. In fact, the acceptance of technology is one of the most crucial concerns when it comes to modifying employees' attitudes (Lambert et al., 2023; Zahidi et al., 2024). The new AI technologies are already reshaping organisations and bringing about changes in employees' behaviour, which is why this study also draws insights from the DIT. As noted by Turan (2019), the DIT seeks to characterise acceptance patterns and explain the structure of innovation use in order to predict how individuals choose which innovations to adopt (Dwivedi et al., 2017). According to the DIT model, the use of AI by employees in sustainable tourism businesses depends strongly on societal influence.

The acceptance of AI technology by tourist establishments depends on whether their employees perceive it as efficient, particularly when it comes to performance expectancy. DeLone and McLean (2003) define performance expectancy as the confidence an employee has that using a particular technology will enhance their capacity to perform tasks. This confidence plays a crucial role in determining whether employees will embrace AI as a valuable tool in their work processes. When employees believe that AI can significantly boost their performance, they are more inclined to integrate these technologies into their daily routines. This is supported by Schukat and Heise (2021), who claim that users' performance expectations are the foremost factors in evaluating their intention to use new technologies. In the tourism sector, where customer experience and service efficiency are paramount, the perceived advantages of AI can transform an employee's approach to their job, leading to improved service delivery and operational efficiency. Furthermore, organisations must recognise that the perceived benefits of AI are not just theoretical; they are central to gaining employee buy-in. If workers can see tangible benefits such as increased productivity, enhanced customer interactions, and a decrease in mundane tasks, they are considerably more likely to accept and effectively use AI tools. Conversely, if employees lack confidence in the technology's ability to enhance their performance, resistance and hesitation towards AI adoption will likely ensue, hindering potential innovations within the organisation. To cultivate an environment where AI is welcomed, it is critical for leadership to actively engage with employees. By addressing concerns and providing clear examples of how AI can foster improved performance, organisations can nurture a positive attitude toward technology adoption. Thus, it follows that employees' expectations regarding the performance of AI technologies significantly affect their acceptance and utilisation of these tools. In view of the above, the following hypothesis was formulated:

H1: Performance expectancy has a positive effect on employees' behavioural intentions.

The successful integration of AI systems in the workplace also depends on effort expectancy. As Choi (2021) points out, the ease with which employees can utilise technology is paramount. User-friendly design encourages widespread adoption, whereas complex systems can lead to reluctance or even outright rejection. This observation is particularly crucial in industries like tourism, where the efficiency and effectiveness of AI tools can significantly impact operations and service delivery. The argument for prioritising effort expectancy is further supported by Turan (2019), who notes that employees are more inclined to embrace technological systems that enhance their work performance. This suggests that when AI systems are designed with usability in mind, they are more likely to be accepted and utilised effectively. In contrast, if an AI system fails to consider the skills and capabilities of its users, it may become an obstacle rather than a facilitator of productivity. Moreover, the potential for AI to become a complex and inflexible tool in the hands of employees cannot be overlooked. If such systems are not implemented with an understanding of users' needs and the context in which they operate, they could hinder rather than enhance workers' abilities to perform their tasks. This inflexibility not only stifles innovation but also breeds frustration among employees, leading to a decline in morale and overall work performance. Therefore, it is imperative to recognise that effort expectancy is not merely a theoretical concept but a crucial factor in the practical acceptance of AI in the workplace. An emphasis on user-friendly design is essential for fostering a culture of acceptance and maximising the potential benefits of AI technologies. Given these considerations, another hypothesis was proposed:

H2: Effort expectancy has a positive effect on employees' behavioural intentions.

The concept of social influence plays a key role in the acceptance of new technological systems in the model developed by Venkatesh et al. (2003). They argue that the degree to which individuals perceive guidance from significant others greatly affects their likelihood of embracing innovation. While this perspective is valuable, it raises an important question: should individuals be so heavily swayed by their social networks when deciding to adopt new technologies?

Further support for the power of social influence can be found in a study by Vannoy and Palvia (2010), who explore how a person's social network significantly shapes their acceptance of technology. However, one could argue that this reliance on peer pressure may inhibit personal judgment. When a technology is adopted solely because of social dynamics, it may not align with an individual's genuine needs or preferences. Thus, it is crucial to critically assess whether conformity is truly advantageous for individual growth or merely a symptom of social dynamics. Talukder's (2012) definition highlights the tendency of individuals to adopt an innovation to conform; yet this conformity often implies a loss of individuality in decision-making. When people feel compelled to follow influential figures within their networks, is it possible that they are sacrificing their unique perspectives for the sake of acceptance? The fear of being left behind or not fitting in can suppress innovative thinking and personal agency. Alblooshi and Hamid (2021) argue that mandatory use can intensify social influence, especially in contexts where knowledge about the technology is limited and rewards or penalties are in place. The risks of coercive adoption could lead to dissatisfaction and disengagement in the long run. Ultimately, while social influence undeniably shapes the technological landscape, it is critical to recognise its dual nature. While it can serve as a catalyst for acceptance, it may also undermine personal judgment and foster a culture of conformity. Therefore, individuals and organisations must strive to balance social influence with personal autonomy in their approach to adopting new technologies. Acknowledging this balance is essential to fostering an innovative environment that empowers individuals rather than stifling their creative potential. The above considerations are the basis for the following hypothesis:

H3: Social influence has a positive effect on the behavioural intentions of employees.

The role of facilitating conditions in shaping employees' adoption of AI is an understudied yet crucial aspect of organisational dynamics. It is well-documented that when individuals perceive the existence of an organisational and technological framework conducive to the use of AI, they are more willing to use it (Venkatesh et al., 2003). However, the observation that facilitating conditions impact use behaviour more significantly among older employees, particularly those with extensive experience, raises important considerations about age and adaptability in the workplace (Venkatesh et al., 2003). This demographic could be particularly resistant to change, and their behaviour may be more strongly influenced by the perceived support systems provided by their organisation. Conversely, it is concerning that these enabling conditions do not seem to affect employees' behavioural intention. This dissonance highlights a potential gap in how organisations communicate and promote AI adoption. If employees recognise the support systems available but do not feel inclined to integrate the technology into their daily tasks, there is a critical need for organisations to address the cultural and motivational aspects surrounding AI. Furthermore, the assertion that enabling conditions can predict use behaviour but not intent (Talukder, 2012) raises significant questions about the nature of employee engagement with AI technologies. This suggests that organisations may place too much focus on establishing technological infrastructure without adequately fostering an environment that encourages intentional adoption. It is not enough to create enabling conditions; there must also be an effort to cultivate a culture of innovation and openness that genuinely engages employees and prompts them to adopt AI actively. In light of the above, organisations must not only ensure that facilitating conditions are in place but should strive to create a holistic environment that motivates and inspires employees to embrace AI, thus maximising the potential benefits of technological advancements. Without such efforts, even the most robust enabling conditions may fall short in achieving widespread and effective AI adoption. In view of the above, the following hypothesis was proposed:

H4: Facilitating conditions have a positive effect on employees' behavioural intentions.

The concept of relative advantage is a critical component of the Diffusion of Innovations Theory (DIT), as emphasised by Frick et al. (2021). Relative advantage refers to the degree to which an invention is perceived to outperform the existing technology it aims to replace, especially in terms of cost, efficiency, or reputation (Cao et al., 2021). This perspective is vital because it underscores the necessity for new technologies to demonstrate tangible benefits over their predecessors. It is essential to note that merely introducing a new technology is not sufficient for its adoption. Employees are significantly influenced by their perceptions of a technology's efficacy and value. When individuals recognise the advantages of a new tool, specifically its ability to enhance their work processes compared to systems used so far, they are more inclined to embrace it. This alignment between perceived usefulness and efficiency is crucial, as it directly impacts people's willingness to adopt new technologies (Scott et al., 2008). In short, the concept of relative advantage is not just relevant theoretically but is also a practical guide for organisations seeking to implement new technological tools. If businesses can effectively communicate and demonstrate the superiority of new innovations, they are likely to foster a more receptive attitude among employees, ultimately leading to successful technology adoption. Thus, the following hypothesis was proposed:

H5: Relative advantage has a positive effect on employees' behavioural intentions.

The compatibility of technology with user needs, values, and experiences is a critical factor in determining its acceptance and success. As Scott et al. (2008) note, technology that aligns with the expectations and backgrounds of potential users is more likely to gain acceptance. This principle is especially relevant in discussions around emerging technologies, such as artificial intelligence and autonomous vehicles. Lutfi et al. (2022) argue that compatibility is not merely about functional alignment; it includes a broader set of values and ideals. Employees are more inclined to adopt AI systems if these tools resonate with their own values and past experiences. If a technological tool appears incompatible, it can lead to frustration and resistance, as individuals may perceive it as undermining their established ways of working. Chen et al. (2021) examine this notion in the context of autonomous vehicles. They found that individuals who thought these vehicles would seamlessly integrate into existing transportation systems were more inclined to support their implementation. This underscores the importance of perceived compatibility, which can influence public opinion and acceptance of new technologies. However, one cannot overlook the risk of resistance when technologies fail to connect with users' values and experiences. The challenge lies in ensuring that new innovations are designed with user compatibility in mind. This means understanding the intricacies of user backgrounds and their experiences with similar technologies, which ultimately affects their perception of a technology's usefulness and ease of use. Therefore, the greater the compatibility of a technology with users' values, desires, and experiences, the higher the likelihood of its acceptance and successful integration into everyday use. This highlights the need for developers and policymakers to prioritise user-centred design in technological advancements to foster a more inclusive and effective technological landscape. In view of the above, the following hypothesis was formulated:

H6: Compatibility has a positive effect on employees' behavioural intentions.

In the context of technological implementation, complexity is often compared to perceived usability, which describes a system that is easy to learn and requires minimal effort from employees (Turan, 2019). For AI to be adopted successfully, users must learn about, understand, and become aware of how it functions and advantages it offers. As a result, users will prefer AI systems that are less labour-intensive and easier to understand and use. Lambert et al. (2023) describe complexity as the difficulty of comprehending and utilising new innovations. The complexity of AI reflects employees' or organisations' perceptions of its accessibility and ease of use, indicating whether the technology is user-friendly. Furthermore, the complexity of the technology can lead to misunderstandings regarding its intended purpose (Morandini et al., 2023). Similarly, the implementation of complex AI systems can negatively affect employees' willingness to use AI in sustainable tourism (Freitas et al., 2023). These considerations led to the formulation of the following hypothesis:

H7: Complexity has a negative effect on employees' behavioural intentions.

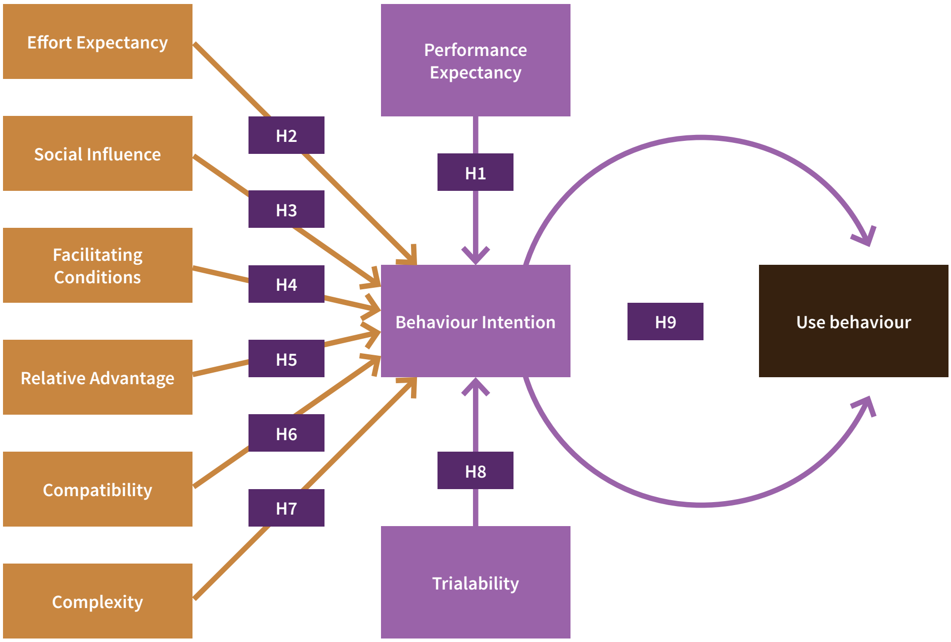

Figure 1. Proposed model
Source: Authors

Trialability is another factor that plays a crucial role in the successful adoption of innovations like AI within the tourism industry. Defined as the ability to test a technology without significant risk or cost, trialability allows gradual implementation, which can foster positive outcomes (Talukder, 2018). Wolske et al. (2017) highlight that assessing AI before its widespread use is essential; if employees find AI difficult to use or irrelevant, their perceptions can turn negative. Thus, providing employees with the opportunity to trial AI enhances their understanding and confidence in the technology, leading to increased productivity and better service. The positive impact of trialability becomes especially important in overcoming resistance to new technologies, as it helps build a culture of innovation and adaptability. As a result, trialability is vital for tourism businesses to ensure the successful integration of AI. By allowing employees to test and adapt to AI solutions, organisations can address concerns and enhance acceptance, ultimately leading to improved operational outcomes. Thus, the following hypothesis was developed:

H8: Trialability has a positive influence on employees' behavioural intentions.

Behavioural intention serves as a crucial predictor of individual actions, encapsulating not just the likelihood of engaging in a specific behaviour but also the underlying motivations driving that choice (Ajzen, 1991). This concept is particularly relevant in technology adoption research, where understanding these intentions can lead to more effective interventions. If we acknowledge the impact of behavioural intentions on actual behaviour, it becomes essential to examine and measure these intentions to facilitate positive changes and encourage technology use. Therefore, the following hypothesis was put forward:

H9: Behavioural intentions have a positive effect on use behaviour.

Figure 1 shows relationships between the above hypotheses.

4. Material and Methods

4.1. Instrument Development and Data Collection

The following study employed a quantitative research design grounded in positivism and a deductive approach. An online questionnaire was used to collect data from a self-selected sample of 353 employees of tourism organisations operating in South Africa's Gauteng province, which have implemented AI systems. The questionnaire consisted of existing validated measurement scales for key constructs, such as performance expectancy, effort expectancy, social influence, facilitating conditions, relative advantage, compatibility, complexity, and trialability, which were derived from the literature (Alblooshi & Hamid, 2021; Cao et al., 2021; Chatterjee et al., 2021; Frick et al. 2021; Bajunaied et al., 2023; Gursoy et al., 2019; Dwivedi et al., 2017; Cheung & Vogel, 2013). Of the 400 questionnaires received, only 353 were deemed suitable for further analysis following data screening. Partial least squares structural equation modelling (PLS-SEM) techniques were applied to analyse the data to investigate the potential relationships between variable outcomes and use behaviour. The validity and reliability of the measurement models were assessed, and the fit and significance of the paths in the structural model were evaluated.

4.2. Statistical Methods

The study examined the proposed relationships between the constructs using partial least squares structural equation modelling (PLS-SEM). PLS-SEM is a useful technique for evaluating large data sets since models typically become more complicated as the number of observations increases (Ringle et al., 2014). Additionally, exploratory research and theory development are two areas where PLS-SEM excels (Hair et al., 2017). Because PLS-SEM maximises explained variance and possesses greater statistical power in parameter estimates, it was chosen over covariance-based SEM (Tajvidi et al., 2018). The study by Diamantopoulos and Winklhofer (2001) employed a reflective measurement model, where it is assumed that changes in latent variables are reflected in changes in their indicators, so modelled relationships run from latent variables or constructs to indicators or observed variables.

4.3. Respondents' Profiles

In terms of age, 204 respondents (57.8%) were aged 18–30, 84 (23.8%) — aged 31–40, 44 (12.4%) — aged 41–50, and 21 (6%) — aged 51 and older. 153 (43.2%) identified themselves as women, 139 (39.2%) as male, while 35 (10.2%) preferred not to disclose their sex. As regards the level of education, 159 (45%) respondents had completed high school, 84 (23.8%) had a bachelor's degree, while 29 (8.2%) held a master's degree. Respondents were also asked to provide information about their experience of using AI tools. 119 (33.7%) reported having one year of experience, while 43 (12.2%) said they had over five years of experience. The final question in this section was about the type of AI tool they had used. 145 (41.1%) mentioned chatbots, while 79 (22.4%) indicated seamless booking systems.

5. Results

5.1. Validity and Reliability of the Constructs

To confirm the validity and reliability of the construct measures in Table 3, the measurement model was assessed prior to examining the structural model in Figure 2. Composite reliability (CR) was utilised to evaluate the dependability of the reflective constructs; values exceeding 0.7 indicated adequate reliability (Nunkoo & Ramkissoon, 2012).

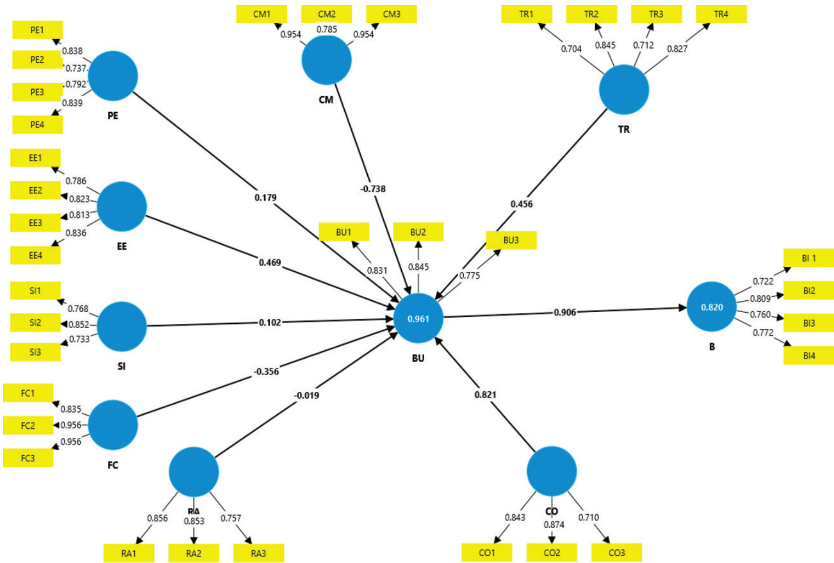

Fig 2. The structural model
Source: Authors

Composite reliability and average variance extracted (AVE) were employed to evaluate the outer model's internal consistency and convergent validity, respectively. As composite reliability accounts for the various outer loadings of the indicator variables, it serves as a useful metric for assessing internal consistency reliability (McCrae & Costa, 1989). In relation to the extent of variance caused by the measurement error, the AVE indicates the average amount of variance that a latent construct captures from its indicators (Fornell & Larcker, 1981). In other words, it measures the extent to which the indicators represent the latent construct they are intended to assess. According to the general rule, a latent construct is deemed to have sufficient convergent validity if it explains at least 50% of the variance of its indicators given a threshold of 0.5. Cronbach's alpha assumes that each indicator is equally reliable (Ringle et al., 2014). All items demonstrated convergent validity, with over 50% of each item's variance shared with its corresponding construct, thereby indicating that all questionnaire items were satisfactory and reliable. Furthermore, all individual item loadings exceeded the recommended value of 0.7. The lowest AVE value of 0.711 is also above the recommended threshold of 0.4, and the lowest composite reliability value of 0.828 is significantly higher than the recommended value of 0.6. These findings generally indicated that the research instrument exhibited acceptable levels of reliability.

Table 1. Measurement accuracy assessment

Factors and items	Factor Loading	Composite Reliability	Average Variance Extracted (AVE)	Cronbach Alpha	Variance Inflation Factor (VIF)	Standard Deviations (STD)
Performance expectancy		0.878	0.814	0.814		
PE1: I believe AI would be useful in my daily work.	0.838				1.896	0.874
PE2: My interaction with the AI would be clear and understandable.	0.737				1.436	0.798
PE3: I trust AI as a critical tool for my work.	0.792				1.659	0.915
PE4: I utilise AI because it improves work productivity.	0.839				1.991	0.878
Effort expectancy		0.887	0.783	0.831		
EE1: I find AI technologies relatively easy to use.	0.786				1.635	0.906
EE2: Understanding and learning to use AI would be simple for me.	0.823				1.848	0.874
EE3: AI is user-friendly.	0.813				1.813	0.915
EE4: I like AI because it makes my job easier.	0.836				2.001	0.878
Social influence		0.828	0.785	0.702		
SI1: People around me (co-workers, family/ friends) believe I should use AI.	0.768				1.407	0.878
SI2: I intend to share and encourage co-workers to use AI technologies.	0.852				1.316	0.847
SI3: I employ AI as a result of my colleagues' assistance.	0.733				1.395	0.889
Facilitating conditions		0.941	0.841	0.903		
FC1: I have the resources required to employ AI.	0.835				1.677	0.874
FC2: My organisation has established support systems for AI learning.	0.956				1.369	0.878
FC3: My experience allows me to effortlessly grasp and apply AI technologies.	0.956				1.369	0.878
Relative advantage		0.863	0.711	0.762		
RA1: I believe that AI would be more efficient and advanced than my current technology.	0.856				1.711	0.878
RA2: I am willing to try new AI technologies despite the cost.	0.853				1.656	0.848
RA3:AI should be costly due to its intelligence and data quality.	0.757				1.395	0.896
Compatibility		0.852	0.743	0.743		
CO1: AI is reliable for offering consistent products and services.	0.843				1.574	0.920
CO2: Using AI is influenced by my values.	0.874				1.734	0.847
CO3: I utilise AI because it meets my needs, wants, and experiences in the workplace.	0.71				1.338	0.906
Complexity		0.928	0.812	0.880		
CM1: I am comfortable and confident using the AI systems.	0.954				1.561	0.906

Factors and items	Factor Loading	Composite Reliability	Average Variance Extracted (AVE)	Cronbach Alpha	Variance Inflation Factor (VIF)	Standard Deviations (STD)
CM2: The use of AI helps me to integrate important information.	0.785				1.465	0.915
CM3: I received training to understand AI systems.	0.954				1.561	0.906
Trialability		0.856	0.766	0.779		
TR1: I am the first to test out new AI tools at work.	0.704				1.456	0.995
TR2: I am more likely to employ AI after it has been tested by the organisation and others.	0.845				1.615	0.885
TR3: I want to be allowed to employ AI on a trial basis to see what it can do.	0.712				1.556	0.896
TR4: The use of AI tools is time-consuming but brings positive results.	0.827				1.909	0.906
Use behaviour		0.858	0.753	0.751		
BU1:AI helps me keep up with my work.	0.831				1.597	0.920
BU2: Regular use of AI enables me to deliver superior service.	0.845				1.716	0.876
BU3: Using AI allows me to avoid mistakes and not neglect job tasks.	0.775				1.365	0.885
Behavioural intention		0.850	0.750	0.770		
BI1: The use of AI is a good idea.	0.722				1.512	0.995
BI2:AI-supported decision-making has had a positive impact on my career growth.	0.809				1.587	0.885
BI3: Using AI increases my chances of making significant decisions.	0.76				1.614	0.906
BI4I : Plan to use AI frequently.	0.772				1.341	0.920

Source: Authors

According to Ringle et al. (2014), discriminant validity refers to the extent to which a latent construct differs from other latent constructs in a given study. The Fornell-Larcker criterion is the most commonly employed method for assessing discriminant validity. The value of AVE for each construct must exceed its shared variance (Fornell & Larcker, 1981).

The outcomes of the Fornell-Larcker criterion are presented in Table 2. As can be seen, the results for discriminant analysis in the table indicate that the square root of every component AVE is bigger beyond its association to a different component. As stated by Hanafiah (2020), every construct's average variation should be greater than its squared correlation between all other constructs. Table 2 displays the diagonal values in bold; the figures reveal that the highest square root of the AVEs is 0.917, while the lowest is 0.862.

Table 2. Discriminant validity according to the Fornell-Larcker criterion

	BI	BU	CM	CO	EE	FC	PE	RA	SI	TR
(BI)	0.866									
(BU)	0.706	0.868								
(CM)	0.587	0.432	0.901							
(CO)	0.675	0.639	0.534	0.862						
(EE)	0.599	0.512	0.684	0.539	0.885					
(FC)	0.475	0.442	0.537	0.514	0.610	0.917				
(PE)	0.546	0.510	0.553	0.582	0.649	0.618	0.902			
(RA)	0.504	0.467	0.518	0.548	0.559	0.554	0.574	0.873		
(SI)	0.559	0.643	0.500	0.556	0.619	0.545	0.559	0.552	0.886	
(TR)	0.622	0.571	0.650	0.635	0.624	0.476	0.552	0.572	0.615	0.875

Source: Authors

5.2. Model Evaluation

To identify common method bias in PLS-SEM, researchers utilise a full collinearity assessment method. To evaluate collinearity, they examine values of Variance Inflation Factor (VIF). According to Diamantopoulos and Siguaw (2006), VIF values exceeding 3.3 suggest the presence of common method bias (CMB), whereas values below this threshold indicate its absence. The same authors calculated VIF values in accordance with established social science practices rather than directly reporting collinearity issues. The results of the collinearity assessment using VIF values are shown in Table 1. As can be seen, VIF values for all constructs are below 3.3, which indicates the absence of CMB in the study. Furthermore, goodness-of-fit was assessed using the Standardised Root Mean Square Residual (SRMR), which is calculated as the square root of the mean of the squared standardized residuals between the observed and predicted covariance matrices (Chen, 2007). An SRMR value of less than 0.08 indicates a good model fit, so the result of 0.07 obtained in the study indicates an adequate fit. The Normed Fit Index (NFI), which compares the chi-square values of the proposed model and the null model was also 0.87, which meets the suggested NFI thresholds (Hu & Bentler, 1999). The adequacy of the model is further substantiated by these findings.

Another element of the model evaluation involved examining coefficients of determination (R^2) of the endogenous constructs. According to Schumacher et al. (2016), the R^2 value represents the percentage of variance in a variable that can be explained by the independent variables. Hair et al. (2019) suggest that R^2 values of 0.75, 0.5, and 0.25 can be considered significant, moderate, and weak, respectively. R^2 values were calculated for two constructs analysed in the study:

behavioural intention and use behaviour.. The R^2 values for these constructs were 0.584 and 0.419, respectively. These values indicate that the model has moderate to significant explanatory power (Hair et al., 2019). In addition to R^2 as a prediction criterion, Hair et al. (2017) recommend examining Q^2 to assess the predictive relevance of the structural model. The predictive applicability of constructs should be positive and have values greater than zero (Hair et al., 2019). Q^2 values of 0.02 represent small predictive relevance, 0.15 — medium and over 0.35 — large. In this study, the value of Q^2 for use behaviour was 0.448 and for behavioural intention — 0.335, indicating that the path model has sufficient predictive relevance for the endogenous constructs.

5.3. Hypothesis Verification and Discussion

It was found that performance expectancy has a major has a positive effect on employees' behavioural intentions ($\beta = 0.179$, $p < 0.05$), which means that H1 can be accepted (see Table 3). This finding is consistent with the study by Cao et al. (2021), who note that performance expectancy has repeatedly been involved in multiple paradigms for integrating IT, which has been supported by empirical evidence from different studies conducted in various settings. Furthermore, Chatterjee et al. (2021) found a positive effect of performance expectancy on workers' attitudes towards the use of AI in customer relationship management (CRM) systems.

It was also found that effort expectancy a positive and significant effect on employees' behavioural intention of adopting AI technologies ($\beta = 0.469$, $p < 0.05$), which means that H2 is supported. This finding is consistent with a study by Cao et al. (2021), in which effort expectancy was found to have a positive effect on respondents' behavioural intention to employ AI for organisational purposes. Positive correlations between these two factors were also reported by Chatterjee et al. (2021).

As for the effect of social influence, a statistically significant correlation with behavioural intentions was detected ($\beta = 0.102$, $p < 0.05$), which means that H3 can be accepted. A similar finding was reported by Al-Sharafi et al. (2023), who found that favourable opinions from friends, family, co-workers, and peer groups increase Generation Z's willingness to use AI products in daily and work tasks. Furthermore, a study by Yin et al. (2023) report that organisational characteristics such as organisational AI readiness positively affect employees' attitudes towards AI assistants.

As can be seen in Table 3, a positive and significant effect on employees' use behaviour was also found in the case of facilitating conditions ($\beta = -0.356$, $p < 0.05$), which means that H4 can be accepted. Facilitating conditions refers to the degree to which an individual trusts that an organisational and mechanical infrastructure exists to support use of the system. The significance of facilitating conditions as a predictor of behavioural intentions was reported by Hmoud and Várallyai (2020), who studied attitudes of HR professionals towards the use of an AI-based Human Resources Information System (HRIS). Similarly, the study by Al-Sharafi et al. (2023) indicates that individuals are more likely to use AI products more sustainably when they possess the information and tools they require to do so. The same study suggests that to motivate individuals to use services that align with their lifestyles, it is essential to offer them the support, resources, and skills that they need to do so.

On the other hand, no statistically significant association was found between relative advantage and behavioural intentions ($\beta = -0.019$, $p > 0.05$), which means that H5 has to be rejected. This stands in contrast to the study by Moodley & Sookhdeo (2025), who found relative advantage to be positively associated with behavioural intentions regarding AI. Similarly, Hanji et al. (2023) reported a strong effect of relative advantage on employees' behavioural intentions to use chatbots in the tourism industry. A possible reason for the lack of such an effect in our study could be that some respondents in the sample were accustomed to using older systems and were satisfied with them; as a result, they did not consider AI technologies to be superior to older systems.

Moreover, compatibility was found to have a positive and significant effect on employees' use of AI. Therefore, H6 ($\beta = 0.821$, $p < 0.001$) can be accepted. According to Hmoud and Várallyai (2020), compatibility is a crucial predictor of adoption behaviour when it comes to innovations in the field of information technology (IT). Our study confirms results of the study by Cheung and Vogel (2013), who found that compatibility had a favourable effect on the use and acceptance of collaborative technology.

The study also revealed that complexity has a considerably positive effect on employees' use behaviour regarding AI in tourism organisations. Thus, H7 can be accepted ($\beta = 0.738$, $p < 0.001$). According to Tseng (2025), complexity is a challenge when it comes to using a particular technology. Previous studies suggest that the degree of complexity negatively affects technology acceptance. In other words, complexity determines the degree to which organisations believe AI recruitment tools are challenging to utilise.

As posited in H8, trialability was found to positively and significantly associated with behavioural intentions ($\beta = 0.456$, $p < 0.05$). A similar positive effect was reported by Alateeg et al. (2024), who also found that attitudes of respondents who were previously favourably disposed to AI were reinforced by improving its trialability.

Finally, a significant association ($\beta = 0.906$, $p < 0.001$) was found to exist between use behaviour and behavioural intention to adopt AI tools among employees

(H9). A similar study by Or (2023), show that user acceptance of technology is critical to the effective implementation of technology. Furthermore, attitude is significant when added to the UTAUT model and is a good predictor of intent. Models often conclude that the use of technology is determined by behavioural goals, resulting in how users feel (Hooda et al., 2022).

Table 3. Evaluation of the structural model

	Hypothesis	t-statistic	p-value	Path coefficient	Hypothesis status
H1	PE → UB	3.460	0.001	0.179	Accepted
H2	EE → UB	3.145	0.002	0.469	Accepted
H3	SI → UB	3.039	0.002	0.102	Accepted
H4	FC → UB	4.499	0.000	0.356	Accepted
H5	RA → UB	0.620	0.536	0.019	Rejected
H6	CO → UB	23.086	0.000	0.821	Accepted
H7	CM → UB	8.944	0.000	0.738	Accepted
H8	TR → UB	17.682	0.000	0.456	Accepted
H9	UB → BI	104.241	0.000	0.906	Accepted

Source: Authors

6. Conclusions

6.1. Theoretical Implications

The contributions of this study to theory are significant and multifaceted. Firstly, by invoking the unified theory of acceptance and use of technology (UTAUT) the study creates a more robust framework for understanding technology adoption. This inclusion of UTAUT enables a comprehensive examination of how various factors, such as performance expectancy, effort expectancy, and social influence, interact with the characteristics of innovations and adopters. Secondly, the study offers new theoretical insights by highlighting the importance of user intentions and behaviours, particularly when considering moderating factors like sex, age, and experience. By focusing on these moderating variables, the study deepens our understanding of the nuanced ways in which different demographic groups approach technology adoption. Finally, by combining the DIT, TAM and UTAUT, the study emphasizes the need for a multidimensional approach to technology adoption. Overall, the study contributes to the ongoing discourse in technology adoption theory, paving the way for further research and application in this evolving field.

6.2. Practical Implications

This study offers actionable insights regarding ways of implementing technology in the tourism industry, emphasizing practical steps for improvements in this area. Managers should focus on factors like performance expectations and usability to foster a supportive environment for adoption. Technology enhances customer experiences and streamlines operations; for instance, travel agencies can use CRM systems to better understand client preferences. User-friendly systems that align with staff experiences boost adoption rates, while staff training can increase confidence in using technology. Mobile applications are vital, providing travellers with real-time information, but managing app complexity through intuitive design is essential. Feedback mechanisms enable ongoing improvement and user satisfaction. Infrastructure also plays a key role; strong internet connectivity in tourist hotspots encourages the use of digital solutions. Strategies should cater to different traveller demographics, offering traditional methods for older tourists alongside tech-savvy options for younger ones. Promoting trialability through pilot programs allows stakeholders to experience new technologies with minimal risk, while data analytics can refine marketing strategies. Collaborating with tech firms on security and privacy increases trust in adopting new solutions. Effective communication through webinars and social media is critical to keep stakeholders informed. By addressing these factors and tailoring approaches for diverse users, organizations can significantly boost technology adoption, leading to enhanced operational efficiency, customer satisfaction, and a competitive edge in the tourism industry.

6.3. Limitations and Directions for Future Research

This study relied on data collected via an online questionnaire, which tend to be associated with self-selection bias, which means that respondents who choose to participate differ systematically from those who do not. Another limitation was the sole reliance on quantitative data in the form of Likert items, which constrain respondents' potential inputs. The inclusion of qualitative data from face-to-face interviews, focus groups, or observations would enable participants to provide more nuanced responses regarding the use of AI in tourism organisations.

The study focused exclusively on employees from tourism companies that actually employ AI-powered technology, which means that potentially significant perspectives from tourism organisations that have yet to adopt AI technologies were omitted.

Although the sample included respondents aged from 18 to 60, over half of them were between 18 to 30 years old. This demographic skew may have biased the results by giving more weight to the views and attitudes of the younger generation and underrepresenting those of older respondents.

In the light of the growing popularity of AI solutions worldwide, it is imperative for tourism organisations to enhance their understanding of employee attitudes to undertake necessary measures. Future research could focus on tourists who actively engage with and choose tourism offerings and products with a view to helping organisations comprehend tourists' perceptions of AI, as well as providing valuable insights for marketing departments.

CRediT Authorship Contribution Statement

YK, MMM & TMT: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing — original draft, writing — review & editing.

Declaration of Competing Interest

None.

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Intencje behawioralne pracowników dotyczące wykorzystania sztucznej inteligencji w zrównoważonej turystyce

Streszczenie. Celem badania była ocena wpływu ośmiu czynników kształtujących intencje behawioralne pracowników branży turystycznej dotyczące wykorzystania systemów sztucznej inteligencji w ich środowisku pracy. Badane czynniki obejmowały oczekiwaną wydajność i wysiłek wymagany podczas korzystania z nowych narzędzi, sprzyjające warunki, względną przewagę w stosunku do innych rozwiązań, zgodność z potrzebami użytkowników, złożoność i możliwość wypróbowania nowych narzędzi. Czynniki te zostały wykorzystane jako predyktory intencji behawioralnych i zachowań użytkowych. Dane dotyczące pracowników branży turystycznej do analizy PLS-SEM zebrano przy pomocy ankiety internetowej. Wyniki wskazują na istnienie dodatniej i statystycznie istotnej korelacji między oczekiwaną wydajnością, oczekiwanym wysiłkiem oraz wpływem społecznym z jednej strony, a intencjami behawioralnymi z drugiej. Ponadto stwierdzono, że warunki sprzyjające, zgodność z potrzebami użytkowników, złożoność i możliwość wypróbowania były dodatnio i w sposób statystycznie istotny skorelowane z intencjami behawioralnymi, które z kolei były skorelowane z wykorzystaniem sztucznej inteligencji przez pracowników. Badanie przyczynia się do lepszego zrozumienia, w jaki sposób cechy samych użytkowników wpływają na wdrażanie sztucznej inteligencji, zapewniając tym samym wskazówki dla organizacji próbujących znaleźć optymalną drogę działania uwzględniającą złożone czynniki behawioralne związane ze zmianami technologicznymi.

Słowa kluczowe: sztuczna inteligencja, teoria dyfuzji innowacji, zrównoważona turystyka, ujednolicona teoria akceptacji i wykorzystania technologii