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Adoption of ChatGPT for Travel: An Integrated Model of the Extended Technology Acceptance Model, the Theory of Planned Behaviour and Word of Mouth

Abstract

ChatGPT, a user-based technology, has gained popularity in the tourism industry due to its human-like interaction capabilities. This study investigates the adoption of ChatGPT for travel and aims to address these gaps by integrating the extended technology acceptance model, the theory of planned behaviour, and word of mouth into a comprehensive model. The data were collected from ChatGPT users for travel, using an online questionnaire. Structural equation modelling was applied to the proposed model. The direct and indirect effects between perceived usefulness, perceived ease of use, attitude, behavioural intention, subjective norm, trust, and word of mouth were identified.

Keywords: ChatGPT, extended technology acceptance model, theory of planned behaviour, word of mouth, travel

1. Introduction

The tourism industry, encompassing leisure and travel, is among the largest service sectors globally, and it is closely associated with user-driven technological innovations. One such innovation widely adopted in tourism, as well as in numerous other fields, is ChatGPT. Developed by OpenAI and introduced in late 2022, ChatGPT is a powerful and open-source technology that has begun to establish its presence across various domains, including tourism, industry, and academia. It has spurred substantial innovation and garnered widespread interest within these sectors. ChatGPT has attracted considerable attention and is disseminating rapidly due to its capacity to interact in a human-like manner and comprehend the subtleties of human language. It achieved remarkable popularity, reaching 1 million users within the first five days of its launch and exceeding 100 million users two months thereafter (Keiper et al., 2023). Tourists can utilise ChatGPT for purposes such as booking, trip planning, and throughout all stages of travel. Its role is particularly vital in areas such as destinations, activities, attractions, and points of interest (Carvalho & Ivanov, 2024).

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Several theories and models have previously been employed to explain the adoption of ChatGPT: the technology acceptance model -TAM (Li et al., 2025; Ma et al., 2025), the unified theory of acceptance and use of technology – UTAUT (Budhathoki et al., 2024), and the theory of planned behaviour -TPB (Shi et al., 2024). Although many studies on the intention to use ChatGPT in the tourism context have used TAM and TPB (e.g., Li et al., 2025), these theories or models have been independently employed. Therefore, understanding ChatGPT adoption requires a holistic perspective. In addition, with the adoption and use of TAM, the trust factor, which is important in technology acceptance, was added to the model. One of the preconditions for tourists to benefit from AI technology is their perceived trust in its results. TAM, which does not include the trust construct, may be insufficient to fully explain adoption behaviour.

The current study aims to address the gaps outlined above by examining how ChatGPT is adopted for tourism through an integrated model combining the extended technology acceptance model (e-TAM), the theory of planned behaviour (TPB), and word of mouth (WOM). Incorporating TAM into our model offers insights into perceived benefits and ease of use of ChatGPT (Davis, 1989; Davis et al., 1989), while including the TPB provides a thorough understanding of the motivational factors influencing intention and usage behaviour (Ajzen, 1991). Additionally, WOM—which is an effective and motivating mechanism for the diffusion of products, services, and technological innovations (Dennis et al., 2016; Ahmad et al., 2022)—is integrated into the model. Given the complex nature of the tourism experience, involving numerous decision options and cognitive–emotional considerations, combining these theories, models, and mechanisms yields a more nuanced understanding of travellers' decision-making and behaviour regarding ChatGPT adoption in travel.

The findings of this study will have both theoretical and practical implications. Firstly, it offers a comprehensive explanation of the antecedents of ChatGPT adoption by integrating theories used to explain technology intention, namely e-TAM, TPB, and WOM. Consequently, it presents a model that clarifies the factors influencing users' intention to utilise ChatGPT for travel. Secondly, by incorporating the trust factor into TAM, the literature on users' trust in AI technology and their intention to use ChatGPT is expanded. Finally, this study broadens the scope of technology adoption research by including word of mouth (WOM) as a key mechanism in the diffusion of innovations. As a practical implication, the findings are expected to enhance tourism managers' understanding of the factors that drive users' adoption of ChatGPT.

2. Literature review

2.1. ChatGPT in tourism and travel

Tourists can utilise ChatGPT at various levels within the tourism industry (Li et al., 2025). This form of AI may provide tourists with information, advice, or services before, during, and after their trips. The diverse capabilities of ChatGPT may encourage tourists to use this technology (J. H. Kim et al., 2024). ChatGPT's ability to deliver efficient, high-quality, personalised, and cost-effective travel recommendations raises the prospect of applying this technology in the tourism and hospitality sectors (J. H. Kim et al., 2024; Li & Lee, 2025). Tourists can share their needs and preferences with ChatGPT prior to their trip, receiving personalised advice on many topics, including but not limited to accommodation, food, attractions, and transportation (Carvalho & Ivanov, 2024). During their journey, ChatGPT can assist tourists in solving problems and offering guidance (Li et al., 2025).

2.2. Technology acceptance model (TAM)

The technology acceptance model (TAM), which is widely used to understand individuals' behaviour in technology adoption (Bano & Siddiqui, 2024), was initially developed by Davis (1989) to explain how consumers perceive and adopt new technologies (Ma et al., 2025). TAM has been applied in research on adopting various technologies, such as ChatGPT. Its components include behavioural/cognitive factors, perceived risks, perceived usefulness, and perceived ease of use (Sallam et al., 2023). Previous studies indicate that behavioural intentions (BI) are both directly and indirectly related to personality through the TAM's components (Svendsen et al., 2013). Despite differences among TAM models, it is generally assumed that perceived usefulness (PU) and perceived ease of use (PEU) are the main factors influencing the likelihood and intention to adopt technology (J. H. Kim et al., 2024). Several TAM studies (e.g., Liu & Ma, 2024) emphasise the impact of these two elements on attitudes. Users who perceive technology as useful and relevant are more likely to view it positively (Bano & Siddiqui, 2024).

Consequently, PEU and PU may influence both attitudes (AT) towards new technology and behavioural intentions (Davis et al., 1989). Davis (1989) defines PU as the degree to which a person believes that using a particular technology or system will improve their performance, and it reflects evaluations of the benefits provided by using a technology or system (Davis & Venkatesh, 1996). PEU is defined by Davis (1989) as the degree to which a person believes that using a technology will not be cumbersome or will be easy to use without much effort. It represents the easy learning and use of technology.

Some perspectives propose that, with the widespread acceptance of TAM, it can be supplemented with other constructs such as trust (Sarmah et al., 2021). Theories about trust and technology acceptance have been employed to understand how users perceive and engage with recommendations offered by technology (Ali et al., 2023). Trust is a key factor that significantly influences users' adoption of ChatGPT (Lin et al., 2020). Tourists' willingness to rely on ChatGPT's recommendations is a crucial mechanism driving behaviour, and perceived trust reflects ChatGPT's ability to deliver accurate, truthful, and timely travel information (Ali et al., 2023).

2.3. Theory of planned behaviour (TPB)

For many years, the theory of planned behaviour - TPB (Ajzen, 2002) has been used to study human intentions and behaviours, including those related to technology. TPB, which assumes that individuals' behaviour is driven by their intentions, evolved from the theory of reasoned action (TRA) proposed by Ajzen in 1985. The three core components of TPB—attitude towards behaviour, subjective norm, and perceived behavioural control—can influence behavioural intention (Ajzen, 1985; 1991). Attitude reflects beliefs, ideas, and opinions about a product, service, or application (such as ChatGPT in our study) and indicates behavioural beliefs. Subjective norm pertains to social influence and concerns the extent to which others in an individual's social group or those considered important motivate the behaviour. Perceived behavioural control represents the perceived level of effort, difficulty, or ease involved in performing the behaviour (Ajzen, 1991). Recently, studies using TPB to explore the intention to use ChatGPT in tourism have emerged (Shi et al., 2024), and TPB is often combined with models like TAM to predict technology usage behaviour (Dong et al., 2022). Additionally, research shows that many scholars have examined consumers' adoption of technology by integrating TAM and TPB (Cheng & Cho, 2011; Han et al., 2025). Consequently, this study offers a comprehensive understanding of visitors' willingness to use ChatGPT by linking both theories and employing the relevant constructs to measure the models.

2.4. Word of mouth (WOM) in the diffusion of innovations

The diffusion of innovation is a social process that involves interpersonal communication, social relationships, positive electronic word-of-mouth (e-WOM), and the imitation of behaviours (Ahmad et al., 2022). Word of mouth (WOM) plays a vital role in the rate at which innovations spread and are accepted, significantly influencing individuals' perceptions and decisions (Dennis et al., 2016). Many consumers who adopt or experience new technologies may recommend these experiences to others. In addition to traditional personal or interpersonal WOM, recommendations and positive posts on social media platforms (e.g., Instagram and Facebook) can also promote the diffusion of products, services, and technological innovations (Ahmad et al., 2022). Online posts by consumers about new products or technology are often regarded as more trustworthy than company marketing activities (Rynarzewska, 2019). ChatGPT has rapidly gained worldwide popularity due to factors such as global conditions, ease of use, and perceived usefulness, with a key driver being users sharing their experiences with others (Jo & Park, 2024). Consequently, WOM can significantly impact the spread and adoption of ChatGPT.

3. Proposed model and hypotheses

TAM suggests that perceived ease of use (PEU) can positively influence perceived usefulness (PU), meaning that a technology regarded as both useful and user-friendly, like ChatGPT, is more likely to be adopted (Davis & Venkatesh, 1996). Recent studies (e.g., Lai et al., 2023) support this relationship. For example, Li et al.'s (2025) research on ChatGPT for tour route planning found that PEU positively impacts PU. Based on the principles of TAM and supporting literature, we predict that the ease of use of the user-friendly ChatGPT may affect the perceived benefits. Therefore, we propose the hypothesis:

H1: Perceived ease of use (PEU) positively influences the perceived usefulness (PU) of ChatGPT for travel.

Usage or adoption intention (IN) is shaped by perceived usefulness (PU) and perceived ease of use (PEU); the fundamental assumption of TAM (Davis, 1989; Davis et al., 1989). Davis et al. (1989) indicated PU and PEU influence individuals' perceptions and attitudes toward new technology. In some TAM variations, the attitude was added to the model or combined with TPB, indicating its importance in the comprehensive model (Dong et al., 2022). Hence, PU and PEU have been assumed to be the primary factors influencing the willingness and intention to adopt technology (J. H. Kim et al., 2024). For example, Bano and Siddiqui's (2024) study in the field of smart technologies revealed the positive effects of both PU and PEU on attitude. The relationships between PEU, PU, and attitude have been supported in many previous studies, and we claim that individuals' attitudes (AT) towards ChatGPT will be affected by PU and PEU. Based on these considerations, the following hypotheses were developed.

H2: Perceived usefulness (PU) positively influences attitude (AT) towards using Chat GPT for travel.

H3: Perceived ease of use (PEU) positively influences attitude (AT) towards using Chat GPT for travel.

The influence of PU and PEU on the intention to adopt new technologies has long been recognised. TAM research on various technological innovations and ChatGPT use has shown that the perceived usefulness of the technology (PU) and perceived ease of use (PEU) directly impact the intention to adopt it (Lai et al., 2023). For instance, Pillai and Sivathanu's (2020) TAM study found that PEU and PU had a positive and significant effect on the intention to use teacher robots. In the TAM study by Goh et al. (2023), a positive link was reported between PEU and ChatGPT adoption intention (IN). Furthermore, J. H. Kim et al. (2024) found that both PU and PEU positively influence the intention to use ChatGPT for tourism decision-making. Likewise, in a study on using ChatGPT for tour route planning, Li et al. (2025) discovered that PEU had a positive and significant effect on intention to use. Based on this foundation, the following hypotheses were developed.

H4: Perceived usefulness (PU) positively influences behavioural intention (IN) to use ChatGPT for travel.

H5: Perceived ease of use (PEU) positively influences behavioural intention (IN) to use ChatGPT for travel.

User trust, an extension of interpersonal trust, refers to the level of confidence consumers have in the actions or suggestions provided by an artificial intelligence chatbot like ChatGPT (Pham et al., 2024). Trust is a crucial factor influencing users' behavioural intentions towards AI-based services such as ChatGPT (Ali et al., 2023). In the study on the impact of ChatGPT on travel consumer behaviour, the positive effect of trust on usage intention was demonstrated (M. J. Kim et al., 2025). Similarly, in the study conducted by Pham et al. (2024) on the use of ChatGPT in travel services, trust was found to have a positive effect on continuance usage intention. In the current study, we therefore hypothesise that trust in ChatGPT positively influences users' intention to use it.

> *H6:* Trust (TR) positively influences the behavioural intention (IN) to use ChatGPT for travel.

Subjective norms (SN) are factors that can influence individuals' intention to adopt new technologies (Ajzen, 1991) and include topics such as expectation, awareness, social learning, social facilitation, imitation, and recommendation (Ajzen & Fishbein, 1980). Furthermore, SN can be regarded as one of the basic stimulus variables that might affect a person's decisions based on their beliefs and expectations (Xu et al., 2024). If members of a tourist's social network find ChatGPT valuable for enhancing their travel experience and thus recommend its use, this social influence can shape tourists' perceptions of its worth. In a study exploring the adoption intention of ChatGPT, a positive relationship was observed between social influence and adoption intention (Jo & Bang, 2023). Additionally, a study by Shi et al. (2024), conducted on individuals who used ChatGPT to search for travel information, reported a positive impact of subjective norm on usage intention. Therefore, we predict that SN has a positive effect on ChatGPT usage intention (SN) for travel. Consequently, the following hypothesis was developed.

> *H7:* The subjective norm (SN) positively influences the behavioural intention (IN) to use ChatGPT for travel.

Based on the TPB, the SN represents an individual's perception of whether the environment approves of the behaviour (Ajzen & Fishbein, 1980). Thus, SN indicates the pressure or expectation placed on the individual by others to demonstrate the desired behaviour, which can positively influence WOM. When someone's circle of friends or peer group endorses ChatGPT, it can significantly impact their behaviour. Indeed, the positive effect of SN on WOM was supported by the study conducted by Md Husin et al. (2016). Our current study in the travel context expects that WOM may be influenced by SN. Therefore, the hypothesis developed is as follows:

> *H8:* Subjective norm (SN) positively influences word-of-mouth (WOM).

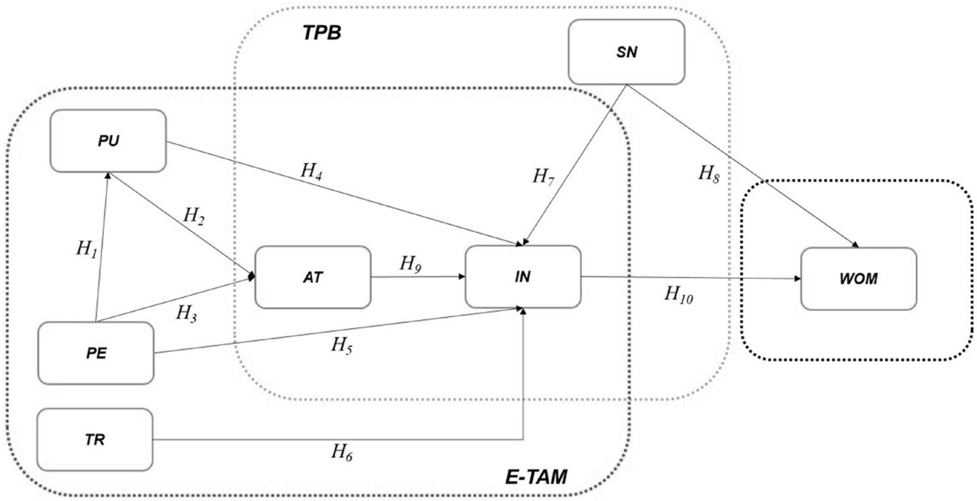
Attitude, which reflects a positive or negative psychological tendency towards a particular person, object, or situation (Koverola et al., 2022), significantly affects usage intentions. This aligns with the core principle of TPB, highlighting the influence of attitude on intention (Ajzen & Fishbein, 1980; Ajzen, 1991). Attitude towards technology is crucial in adoption and intention, influencing decisions about technologies such as ChatGPT (Pham et al., 2024). Previous research (e.g., Zhang et al., 2025) supports the idea that people's attitudes towards a phenomenon shape the adoption of new technologies. The TAM study on attitudes towards AI (Zhang et al., 2025) revealed that individuals with high-performance expectations showed strong behavioural intentions towards artificial intelligence across various sectors and industries (Li, 2023). Moreover, WOM acts as a stimulus affecting users' perceptions and decisions when adopting new technologies (Jo & Park, 2024). Extensive research indicates that WOM stems from satisfaction derived from experiences and subsequent behavioural intentions (Jo & Park, 2024). For instance, M. J. Kim et al. (2025) examined the impact of ChatGPT on travel consumer behaviour and found a positive correlation between intention and WOM. Consequently, based on prior studies, we propose that attitude towards ChatGPT and an individual's intention to use it may influence WOM. Building on the literature and arguments above, the following hypotheses were formulated.

H9: Attitude (AT) towards ChatGPT positively influences the behavioural intention (IN) to utilise ChatGPT for travel.

H10: Behavioural intention (IN) to use ChatGPT for tourism positively influences word-of-mouth (WOM).

The proposed integrated model based on E-TAM, TPB, and WOM is illustrated in Figure 1.

Figure 1
Proposed model



3. Research methodology

3.1. Research sample and data collection

The demographic relevant to this study consists of individuals in Turkey who use ChatGPT for their tourism-related needs. Using convenience sampling, a survey method and a questionnaire were utilised from 22 February to 30 April 2024. Data were collected via Google Docs, an online tool, from individuals planning to travel for tourism purposes within the next 12 months. Respondents were informed at the beginning of the questionnaire about the aim of assessing their current understanding of ChatGPT. Consequently, 592 responses were gathered, forming the research sample.

3.2. Instrument

The current research aims to analyse the links between the variables used in the model. Quantitative methods were preferred, with data collected through a survey containing statements about these variables. An instrument was adapted from existing research and consists of eight parts reflecting the study's aim and scope. The *perceived usefulness scale* (four items) was improved by Lu, Zhou, and Wang (2009), while the *perceived ease of use and subjective norm scales* (three items each) were based on research conducted by Beh et al. (2021). Trust and *attitude scales* (three items each) were adapted from Abbas-Naqvi et al. (2020), and lastly, both *behavioural intention and word of mouth scales* (three items each) were measured using the study of Zeithaml et al. (1996). The scales have been proven to have intercultural validity and reliability and are frequently used in the field. Translations were assessed by two linguistically qualified academics. A five-point Likert scale, with 1 indicating strongly disagree and 5 indicating strongly agree, was used to measure each scale item.

3.3. Data analysis

The collected data were analysed using partial least squares structural equation modelling (PLS-SEM), which enables researchers to test or formulate hypotheses and identify relationships between variables in the models. To evaluate the mediator variables' role, consistent PLS bootstrapping was employed. The factor structure, participant profile, skewness, and kurtosis values were all determined using SPSS 28. Items of all scales were checked for skewness (<3) and kurtosis (-2 and +2) values before executing the measurement model, thereby confirming normality (Matore & Khairani, 2020). The model's path coefficients and the significance of the factor loadings were tested using a bootstrap approach with 5,000 samples. The model was tested with Smart PLS 4.0 software (Ringle et al., 2024), which disregards sample size and normality assumptions and focuses on prediction accuracy in the measurement and structural model analysis. Therefore, the model was evaluated using PLS-SEM as recommended by several researchers (Shumeli et al., 2019).

4. Research findings

This study surveyed 592 ChatGPT users involved in touristic services, with participants' profiles outlined in Table 1. The sample consists of an equal number of women and men (both 296, 50%). Fewer participants use ChatGPT for tourism-related research (27.7%), and the majority hold postgraduate degrees (67.2%). Most are aged 18–25 (55.7%), with an average income of "15,000 TL (Turkish Lira) and below" (36.1%). Since young individuals are well known for adopting new trends like artificial intelligence, technology, and the internet, the age group of 18 to 25 makes up the largest segment in this study, which focuses on those engaging with ChatGPT.

Table 1
Participant's profile

Variable	Group	n	%
Gender	Female	296	50.0
	Male	296	50.0
Age	18-25	330	55.7
	26-35	127	21.5
	36-45	94	15.9
	46-55	36	6.1
	56 and above	5	0.8
Income	15,000 TL and below	214	36.1
	15,001 to 30,000 TL	209	35.3
	30,001 to 45,000 TL	96	16.2
	45,001 to 60,000 TL	42	7.1
	60,001 TL and above	31	5.2
Education	Primary school	18	3.0
	Secondary school	48	8.1
	Undergraduate	128	21.6
	Postgraduate	398	67.2

4.1. Assessment of the measurement model

To test the hypotheses and demonstrate the correctness of the model, Smart PLS was used. To evaluate the measurement model, convergent validity, discriminant validity, and internal consistency reliability were established. The results of our model testing, conducted through confirmatory factor analysis (CFA), are presented with $\chi 2/df$ (4.23), RMSEA (0.07), SRMR (0.04), CFI (0.96), GFI (0.91), AGFI (0.89), NFI

(0.94), and TLI (0.95); all indicators were appropriate and validated (Hair et al., 2020). Based on the measurement results, all factor loadings are above 0.70, as suggested by previous studies (Vinzi et al., 2010). Table 2 shows the measurement results, with Cronbach's alpha ranging from 0.860 to 0.931, composite reliability (CR) ranging from 0.861 to 0.931—both within acceptable levels (Chin, 2010)—and the average variance extracted (AVE) ranging from 0.781 to 0.878, indicating that construct validity was satisfactory (Hair et al., 2019).

Table 2
Measurement model

Construct	Item	Outer Loading	CR	rho-a	AVE	Alpha
Perceived of usefulness (PU)	PU1	0.923	0.931	0.949	0.823	0.928
	PU2	0.880				
	PU3	0.926				
	PU4	0.900				
Perceived of ease of use (PEU)	PEU1	0.894	0.861	0.915	0.781	0.860
	PEU2	0.886				
	PEU3	0.872				
Subjective norm (SN)	SN1	0.924	0.921	0.950	0.863	0.920
	SN2	0.939				
	SN3	0.923				
Trust (TR)	TR1	0.908	0.919	0.947	0.857	0.917
	TR2	0.943				
	TR3	0.927				
Attitude (AT)	AT1	0.936	0.899	0.937	0.833	0.899
	AT2	0.931				
	AT3	0.871				
Behavioural intention (IN)	IN1	0.941	0.931	0.956	0.878	0.931
	IN2	0.940				
	IN3	0.930				
Word of Mouth (WOM)	WOM1	0.901	0.891	0.931	0.819	0.889
	WOM2	0.911				
	WOM3	0.903				

Note. n=592 CR: Composite reliability; AVE: Average variance extracted.

4.1.1. Discriminant validity

To ensure discriminant validity, the Fornell-Larcker method (Fornell & Larcker, 1981), which is a common approach in previous research (Ali et al., 2018), was utilised. The findings from the Fornell-Larcker calculation are shown in Table 3, indicating that discriminant validity was established because the square root of AVE between each pair of components exceeded the expected correlation between factors. The values should be less than 0.90 or 0.85. Since Table 3 shows that the values are below 0.90, convergent and discriminant validity were confirmed in the current study. To assess both multicollinearity and common method bias, we employed not only Harman's single-factor test but also full collinearity as a more rigorous statistical technique (Kock & Lynn, 2012; Kock, 2017). Factor analysis was used to perform Harman's single factor test, where all items were placed into a single factor (Harman, 1976). Less than 50% of the variance was explained by the factor loading of each item. The total variance accounted for by a single factor across all data points was found to be 25.18%, demonstrating that the study is valid concerning common method bias (Podsakoff et al., 2003). Additionally, the multicollinearity assessment conducted shows that there is no multicollinearity problem (Gwelo, 2019; Tsagris & Pandis, 2021; Subhaktiyasa, 2024).

Table 3
Fornell-Larcker criterion values

Constructs	1	2	3	4	5	6	7
Perceived of usefulness (PU)	**0.907**						
Perceived of ease of use (PEU)	0.610	**0.884**					
Subjective norm (SN)	0.547	0.545	**0.929**				
Trust (TR)	0.700	0.593	0.545	**0.926**			
Attitude (AT)	0.847	0.669	0.582	0.721	**0.913**		
Behavioural intention (IN)	0.697	0.642	0.604	0.656	0.775	**0.937**	
Word of Mouth (WOM)	0.701	0.629	0.639	0.695	0.760	0.855	**0.905**

Note. The square roots of AVE for each dimension are represented by the values on the diagonal (bolded).

4.1.2. Structural model and hypothesis testing

The outcomes of the measurement model can be used to analyse the research's structural model (Purwanto & Sudargini, 2021). The Variance Inflation Factor (VIF) values were considered for multicollinearity just prior to analysing the structure in the study. Therefore, all VIF values were less than 5 (Kalnins, 2018; Shrestha, 2020), indicating that there were no significant concerns about multicollinearity in the structural model (see in Table 4).

Figure 2
Structural model

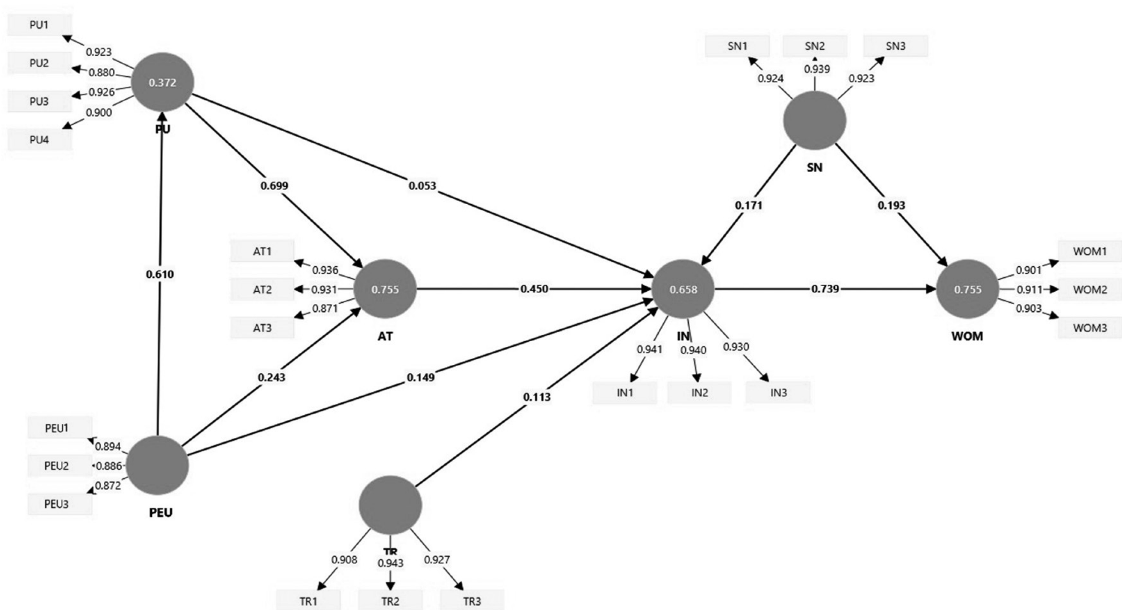


Table 4
Results of path analysis

Hypothesis	β	*t*	*p*	VIF	Hypothesis Testing
H1. Perceived Ease of Use → Perceived usefulness	0.610	19.828	*0.000*	1.000	Supported
H2. Perceived usefulness → Attitude	0.699	25.615	*0.000*	1.591	Supported
H3. Perceived Ease of Use → Attitude	0.243	8.257	*0.000*	1.591	Supported
H4. Perceived usefulness → Behavioural intention	0.053	0.926	*0.355*	3.823	Not Supported
H5. Perceived Ease of Use → Behavioural intention	0.149	3.362	*0.001*	1.998	Supported
H6. Trust → Behavioural intention	0.113	2.690	*0.007*	2.388	Supported
H7. Subjective norm → Behavioural intention	0.171	4.429	*0.000*	1.676	Supported
H8. Subjective norm → Word of mouth	0.193	6.385	*0.000*	1.574	Supported
H9. Attitude → Behavioural intention	0.450	8.484	*0.000*	4.423	Supported
H10. Behavioural intention → Word of mouth	0.739	27.553	*0.000*	1.574	Supported

Table 4 and Figure 2 display the results of the measurement model. Based on the data analysis, perceived ease of use significantly affects perceived usefulness (β = 0.610, t = 19.828, $p < 0.05$), and it also influences attitude (β = 0.243, t = 8.527, $p < 0.05$), as well as behavioural intention (β = 0.149, t = 3.362, $p < 0.05$). While perceived usefulness impacts attitude (β = 0.699, t = 25.615, $p < 0.05$), it does not significantly influence behavioural intention (β = 0.053, t = 0.926, p = 0.355). Subjective norm affects not only behavioural intention (β = 0.171, t = 4.429, $p < 0.05$), but also word of mouth (β = 0.193, t = 6.385, $p < 0.05$). Both trust (β = 0.113, t = 2.690, $p < 0.05$) and attitude (β = 0.450, t = 8.484, $p < 0.05$) significantly influence behavioural intention, according to the analysis. Finally, as the last hypothesis proposed, behavioural intention to use ChatGPT for tourism positively influences word-of-mouth (β = 0.739, t = 27.553, $p < 0.05$). In summary, hypotheses H1, H2, H3, H5, H6, H7, H8, H9, and H10 were accepted, while hypothesis H4 was rejected in this study.

4.1.3. Mediation and serial mediation effects

As shown in Table 5, the results of the indirect effects are described as follows. For the indirect effects, attitude mediates both between perceived ease of use and behavioural intention (β = 0.110, $p < 0.05$), and between perceived usefulness and behavioural intention (β = 0.315, $p < 0.05$). Additionally, behavioural intention mediates both between perceived ease of use and word of mouth (β = 0.110, $p < 0.05$), and between attitude and word of mouth (β = 0.334, $p < 0.05$); however, there is no mediation of behavioural intention between perceived usefulness and word of mouth (β = 0.039, p = 0.356). Furthermore, behavioural intention exerts an indirect effect on word of mouth from both subjective norm (β = 0.126, $p < 0.05$) and trust (β = 0.083, $p < 0.05$). Regarding perceived usefulness, it mediates perceived ease of use on attitude (β = 0.426, $p < 0.05$), but not on behavioural intention (β = 0.032, p = 0.359).

Table 5
Indirect effects

Mediation regression coefficient paths	Indirect effects	*S.D.*	*t*	*p*	%95 LLCI	ULCI
PEU → AT → IN	0.110*	0.019	5.731	*0,000*	0.150	0.075
PEU → PU → AT	0.426*	0.026	16.156	*0,000*	0.478	0.376
PEU → PU → IN	0.032	0.035	0.918	*0,359*	0.102	-0.035
PEU → IN → WOM	0.110*	0.033	3.324	*0,001*	0.174	0.045
PU → IN → WOM	0.039	0.042	0.923	*0,356*	0.121	-0.043
PU → AT → IN	0.315*	0.039	8.021	*0,000*	0.395	0.242
AT → IN → WOM	0.334*	0.040	8.287	*0,000*	0.413	0.255
SN → IN → WOM	0.126*	0.028	4.453	*0,000*	0.182	0.070
TR → IN → WOM	0.083*	0.032	2.636	*0,008*	0.146	0.022
PU → AT → IN → WOM	0.233*	0.030	7.858	*0,000*	0.294	0.177
PEU → AT → IN → WOM	0.081*	0.014	5.662	*0,000*	0.111	0.055
PEU → PU → AT → IN	0.192*	0.025	7.557	*0,000*	0.245	0.145
PEU → PU → IN → WOM	0.024	0.026	0.916	*0,360*	0.074	-0.026
PEU → PU → AT → IN → WOM	0.142*	0.019	7.444	*0,000*	0.182	0.106

Note. n=592. *p < 0.01; S.D.: Standard deviation; PEU: Perceived ease of use; PU: Perceived usefulness; intention; AT: Attitude; IN: Behavioural intention; SN: Subjective norms; TR: Trust; WOM: Word of mouth; t: T-Values; LL: Low limit; UL: Upper limit.

Finally, the mediation analysis findings demonstrate serial indirect effects of perceived ease of use on word of mouth through both PEU→AT→IN→WOM (β = 0.081, $p < 0.05$) and PEU→PU→AT→IN→WOM (β = 0.142, $p < 0.05$), but not via PEU→PU→IN→WOM (β = 0.024, p = 0.360). Additionally, there is serial mediation of perceived usefulness on word of mouth via PU→AT→IN→WOM (β = 0.233, $p < 0.05$), and perceived ease of use also serially mediates behavioural intention through PEU→PU→AT→IN (v = 0.192, $p < 0.05$).

5. Discussion

Drawing on extended TAM, TPB, and WOM, the current study examined the determinants influencing the intention to use ChatGPT in tourism travel. The results validate the proposed comprehensive model that incorporates TAM, TPB, and WOM. This conclusion emphasises the importance of the TPB model's interaction in understanding how individuals' behavioural intentions are shaped when they encounter new technology during travel, such as seeking information and receiving advice. The findings align with previous research highlighting the internal significance of TPB variables in determining individual behavioural intentions (Hsu & Huang, 2012; Kusdibyo et al., 2023; Bano & Siddiqui, 2024). The perceived ease of use of ChatGPT may influence whether users see it as useful and, ultimately, their intention to use it. Additionally, PEU and PU were strongly related to attitude, consistent with TAM literature (Davis, 1989; Davis et al., 1989). The results suggest that attitude towards ChatGPT has the greatest impact on intention, a finding also reported by prior studies regarding ChatGPT (e.g., Li, 2023; Zhang et al., 2025). Interestingly, the findings show that the perceived usefulness (PU) of ChatGPT did not have a direct effect on the intention (IN) to use it. Although this contradicts some previous studies (J. H. Kim et al., 2024; Li et al., 2025), it aligns with others (Liu & Ma, 2024) that suggest this effect is mediated by attitude. The study highlights the crucial role of attitude in shaping users' intention to adopt ChatGPT. Indeed, the mediation analysis revealed that attitude towards ChatGPT (AT) mediates the relationship between PU and IN. This implies that tourists' attitudes towards ChatGPT significantly influence their intentions to use it.

Additionally, the findings also revealed that SN had a significantly positive effect on the intention to use ChatGPT, which aligns with the established principles of TPB (Ajzen, 1985; 1991). This result is consistent with the study of Shi et al. (2024), who reported that SN has a positive influence on the intention to use ChatGPT for tourism information searches. Similarly, social influence, which pertains to the influence of important people in one's social network, here SN, demonstrated a positive effect on WOM, as a key factor in the diffusion of innovation.

Another finding of the study involved the role of trust as a determinant of the intention to use ChatGPT. Our results indicated that trust in ChatGPT positively influences the intention to adopt it in tourism travel. This aligns with the studies of Xu et al. (2024) and Ali et al. (2023), which found that trust positively affects the acceptance of ChatGPT in travel services and recommendations. Lastly, the results showed that the intention to use ChatGPT has a strong positive impact on word-of-mouth (WOM). This is consistent with Pasupuleti and Thiyyagura (2024), who found that the intention to recommend ChatGPT among higher education students is influenced by their intention to adopt it.

Regarding the mediating effects, our study confirms that perceived usefulness mediates the relationship between PEU and AT. Similarly, attitudes towards ChatGPT play a mediating role between both PEU and IN, and PU and IN. Additionally, intention functions as a mediator in the relationship between WOM and all constructs within the model. Specifically, intention mediates between WOM and all constructs (AT, PEU, SN, TR), except for the PU-WOM relationship. Moreover, while perceived usefulness and intention do not serve as sequential mediators between PEU and WOM, attitudes towards ChatGPT and the intention to use ChatGPT have a serial mediating effect on PEU's influence on WOM. Furthermore, perceived usefulness and attitudes towards ChatGPT act as sequential mediators in the PEU-IN relationship, whereas the PU-WOM relationship operates through attitudes and intention. Ultimately, three factors (PU, AT, IN) have sequential mediating roles between PEU and WOM.

5.1. Theoretical and practical implications

This study makes several contributions to the literature on tourism and travel. Firstly, the findings offer detailed insights into the hypotheses tested, especially concerning the factors influencing the intention to use

ChatGPT for tourism purposes. It advances research on the intention to use ChatGPT in tourism by proposing a model that combines two theories/models (TAM and TPB) with an innovation diffusion mechanism (WOM). Secondly, this study broadens existing research on adoption antecedents by demonstrating that ChatGPT usage intention is affected by both PU and PEU (TAM) and SN, AT (TPB). Thirdly, by including the trust construct in our TAM model, we emphasise its impact on the intention to adopt artificial intelligence technology. Lastly, this study enhances the literature on the diffusion of innovations by integrating WOM as a mechanism through which individuals can disseminate the relevant technology within their social networks.

This study also provides practical implications for tourism professionals using ChatGPT. Artificial intelligence technologies like ChatGPT can serve tourists, especially since tourism is one of the fastest-growing industries. However, ChatGPT's accuracy and up-to-date information on travel details, such as flights, activity dates, attractions, and others, are limited (Li & Lee, 2025). Therefore, ChatGPT developers need to improve the AI software and algorithms to boost the benefits perceived by travellers. Tourism managers and practitioners can use these findings to develop strategies that promote WOM for ChatGPT adoption. Additionally, this study highlights ways to increase trust in ChatGPT for travel recommendations.

6. Limitations and future directions

This study, while providing valuable insights, has certain limitations to consider for future research. First, future studies should include participants from diverse regions and cultures to produce more generalisable results and enable meaningful comparisons. The second limitation concerns the evaluation of behavioural intention in our model as a proxy for actual use. There is ongoing debate in theories and models, such as TAM and TPB, about whether behavioural intention accurately predicts actual use. Therefore, we recommend further research into ChatGPT usage experiences. Third, anthropomorphic factors such as coolness, warmth, and cuteness may influence the use of ChatGPT for travel (Pham et al., 2024). More comprehensive models that integrate Behavioural Reasoning Theory (BRT), including reasons for and against adoption factors (Al-Qaysi et al., 2025), could provide deeper insights into ChatGPT usage and intentions. Finally, we believe that conducting interactive studies with ChatGPT will offer valuable understanding of actual usage behaviour in tourism.

Declaration of Competing Interests

The authors declare that they have no known competing interests that could have appeared to influence the work reported in this paper.

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