WILL GENERATION Z USE CHATGPT FOR TOURISM RECOMMENDATIONS?

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Abstract

Purpose – This research note examines Generation Z's acceptance of ChatGPT as a Tourism Recommender System, to better understand whether they will use it for a tourism recommendation, and the factors influencing their acceptance.
Methodology/Design/Approach – Grounded in the Technology Acceptance Model (TAM), this research extends the TAM by incorporating Trustworthiness and Perceived Enjoyment to predict Generation Z's acceptance of ChatGPT as a Tourism Recommender System. A Partial Least Squares-Structural Equation Modeling (PLS-SEM) approach was employed to analyse data collected from 150 Generation Z respondents through a validated Likert Scale questionnaire.
Findings – The results reveal that Trustworthiness, Perceived Enjoyment and Perceived Usefulness, influenced Generation Z's Attitude toward using ChatGPT for personalised tourism recommendation. Although there is no direct influence of Perceived Ease of Use on Attitude, it has an indirect effect on Attitude through Perceived Usefulness, which also mediated the influence of Trustworthiness on Attitude.
Originality of the research – The research predicts the acceptance of ChatGPT as a Tourism Recommender System among Generation Z cohort. By extending the TAM with Perceived Enjoyment and Trustworthiness, the study contributed in explaining the Generation Z information search behaviour in relation to ChatGPT, and how it can be enhanced to perform the Tourism Recommender role better.
Keywords ChatGPT, Tourism Recommender System, TAM, Trustworthiness, Enjoyment, Generation Z

Research note
Received 31 October 2024
Revised 24 December 2024
9 January 2025
30 January 2025
Accepted 4 February 2025
https://doi.org/10.20867/thm.31.3.11

INTRODUCTION

The digital age has significantly transformed tourism, presenting opportunities and challenges for travellers. With abundant information on destinations, accommodations, and activities, discerning quality and trustworthiness have become increasingly complex, time consuming and often confusing (Stergiou & Nella, 2024). This situation highlights the need for a reliable tourism recommender system (TRS) to assist travellers in making informed decisions (Nilashi et al., 2017; Wang et al., 2024a).

The development of TRS has been aided by the progress of Artificial Intelligence (AI), with technologies like ChatGPT emerging as notable innovations. Although research on ChatGPT's applications in tourism is still in its infancy, preliminary studies suggest its potential for providing tailored recommendations and disrupting traditional practices (Carvalho & Ivanov, 2024; Mich & Garigliano, 2023; Shin et al., 2023; Volchek & Ivanov, 2024). Other studies raise concerns about tourists' trust in ChatGPT's recommendations (Carvalho & Ivanov, 2024; Chen, 2024; Volchek & Ivanov, 2024) and its impact on their behaviour and decision-making processes (Sigala et al., 2024).

Generation Z is the generational cohort more likely to use ChatGPT for tourism recommendations. Characterised as the technology-savvy cohort born from the late 1990s to late 2000s (Dimitriou & AbouElgheit, 2019; Seyfi et al., 2023), Generation Z represents the future of tourism (Monaco, 2018). As the travellers of tomorrow (Haddouche & Salomone, 2018), their preferences are poised to shape the travel industry significantly, making it essential to understand their behaviour (Puiu et al., 2022), especially when seeking tourism information. Despite their readiness to adopt new technologies (Corbisiero & Ruspini, 2018), research on Generation Z's travel behaviour is rare (Chang et al., 2023; Dimitriou & AbouElgheit, 2019). More importantly, research on Generation Z's use of digital travel-related information remains scarce (Nemec Rudež, 2023). In light of these considerations, this research explores Generation Z's acceptance of ChatGPT as a TRS. It will focus on whether they will likely use it for travel recommendations and identify the factors influencing their acceptance.

Generation Z's acceptance of ChatGPT will be examined using the renowned Technology Acceptance Model (TAM), which posits that users' attitudes toward technology (ATT) are influenced by Perceived Ease of Use (EOU) and Perceived Usefulness (USE) (Davis, 1985). EOU reflects how easy technology is to navigate (Le et al., 2024), while USE indicates its usability to enhance job performance (Le et al., 2024; Solomovich & Abraham, 2024) or to finish a certain task (Vorm & Combs, 2022). TAM also suggests that EOU improves USE through an intuitive interface, intrinsic motivation and perceived enjoyment (Vorm & Combs, 2022).

Recent adaptations of TAM predict AI acceptance by adding variables like Trustworthiness and Perceived Enjoyment. Trustworthiness (TRU) refers to AI's reliability (Wang et al., 2024b), reflected through the willingness of users to accept the risk associated with the technology (Solomovich & Abraham, 2024). Trustworthiness is essential for decision-making in tourism (Dwivedi et al., 2024). Therefore, trust should be established in the development process, deployment, and the use of AI to harness its full potential (Thiebes et al., 2021). Perceived Enjoyment (ENJ) denotes the fun derived from using technology (Al Shamsi et al., 2022; Kowalczyk-Anioł & Nowacki, 2020) apart from its expected performance. Research shows that TRU directly influences user ATT (Choung et al., 2023; Gerlich, 2023) and indirectly affects USE (Al Shamsi et al., 2022), while ENJ directly influences user intention (Al-Adwan et al., 2023; Huang et al., 2024; Wang et al., 2024b) and EOU (Kowalczyk-Anioł & Nowacki, 2020). Eight (8) hypotheses have been formulated based on the literature review.

H_1: ATT toward using ChatGPT as a TRS is positively influenced by ENJ
H_2: ATT toward using ChatGPT as a TRS is positively influenced by EOU
H_3: USE of ChatGPT as a TRS is positively influenced by the EOU
H_4: ATT toward using ChatGPT as a TRS is positively influenced by TRU
H_5: USE of ChatGPT as a TRS is positively influenced by TRU
H_6: ATT toward using ChatGPT as a TRS is positively influenced by USE
H_7: USE meadiating the influence of EOU toward ATT
H_8: USE mediating the influence of TRU toward ATT.

1. METHOD

Following Hair et al. (2014), the sample size of a study utilising PLS-SEM can be determined using Cohen's Power Analysis. The guidelines maintained that to achieve a statistical power of 80% at a significance level of 5%, with an R^2 value of 0.10 and a maximum of four arrows pointing to a single construct, the minimum sample size required is 137. This study analysed data collected from 150 respondents. Hence, based on the aforementioned guidelines, the sample size of this study is statistically sufficient.

Since the study aimed to predict Generation Z's acceptance of ChatGPT for tourism recommendations, the respondents must be selected from the Generation Z cohort with experience in using ChatGPT. Therefore, purposive sampling was chosen to select the respondent. The samples are students of a tourism polytechnic operating two campuses in Bali and Java Island, specifically the students who enrolled in the tourism destination study program. Their understanding of the information the tourist needs to make an informed decision makes them suitable as the respondents to the research. They were asked to participate in the research voluntarily without receiving compensation whatsoever. Even though they did not sign a consent form, the author ensured they were aware of their participation in the research. Out of three hundred and six students, one hundred and fifty returned the questionnaire, making the response rate 49%. Most of the sample was collected on Bali Island (86.7%), while the rest were collected on Java Island. 36.7% of the sample were men, while 63.3% were women, close to the proportion of gender in the target population where 40.1% are men while 59.8% are women. 36% of the samples are in their first year of study, 29% are in their second year, 16% are in their third year, 11% are in their fourth year, and 9% are in their fifth year of study. Since Indonesians usually started their higher education at 18 or 19 years old, none of them were above 25 when the survey took place, thus ensuring that they belong to the Generation Z cohort (Puiu et al., 2022). The survey took place somewhere from February to August of 2024.

A piloted and validated Likert Scale questionnaire was used to collect the data. The questionnaire was typed on Google Forms and distributed online using a Google Forms link. PLS-SEM analysis conducted on SmartPLS 4 was employed to analyse the measurement model, structural model, and the model's predictive power. PLS-SEM is a multivariate statistical technique that has been utilised in various fields of research. It has gained popularity in tourism and hospitality research (Ali et al., 2019) because of its applicability to many types of research, such as causal research (confirmatory and explanatory), predictive, descriptive and exploratory (Henseler et al., 2018). Causal research is based on causal theory, from which a researcher develops the research hypothesis. Unlike causal research, predictive research is not based on causal theory. This kind of research is rare in tourism and hospitality research; therefore, it is usually combined with causal research. Descriptive research is similar to predictive research because it is not based on a causal theory. However, descriptive research has a different aim: to summarize and characterize the data. Exploratory research aims to develop new theories by testing the relationship between constructs that are not necessarily developed based on causal theory. Exploratory research is considered a step toward causal and predictive research that is not necessarily based on a strong causal theory. The current study is behavioural research based on a causal theory, the Technology Acceptance Model. It integrated two constructs into the model designed to predict Generation Z's acceptance of ChatGPT as their source of tourism recommendation. Therefore, this research combines causal, predictive and exploratory research, which is common in tourism and hospitality research (Henseler et al., 2018). Consequently, PLS-SEM is considered the most appropriate technique to be utilised because of its strength in behavioural research paradigm (Henseler et al., 2018; Müller et al., 2018) as well as its strength in prediction (Becker et al., 2023; Sarstedt et al., 2020; Usakli & Kucukergin, 2018) and exploratory research (Ali et al., 2019; Henseler et al., 2018; Latan, 2018).

2. RESULT

2.1. Common method bias

Since the data were obtained from a Likert scale questionnaire, there is a possibility that common method bias may occur (Kock et al., 2021; Kock, 2015). Common method biases are detected using collinearity tests, with a desired VIF value below 3.3, as Kock (2015) suggested, while the highest acceptable value is 5.0 (Hair & Alamer, 2022). The outer model's VIF is ranging from 1.5 to 3.9, while the inner VIF as shown in Table 1 are also below the threshold, therefore there is no indication of significant multicollinearity problems in this study's measurements.

Table 1: **Collinearity Assessment for Common Method Bias**

Construct	VIF
ENJ → ATT	3.7
EOU → ATT	3.0
EOU → USE	1.9
TRU → ATT	2.5
TRU → USE	1.9
USE → ATT	4.7

2.2. Measurement Model Assessment

The model fit was assessed using the Standardized Root Mean Square Residual (SRMR) value, with a desirable threshold of 0.08 (Henseler et al., 2016). This study reports an SRMR value of 0.071, indicating the model's fit with the data. To ensure internal consistency, each item's outer loading must exceed 0.70 (Hair et al., 2019). As shown in Table 2, all outer loadings in this research meet this threshold, demonstrating high correlations with their constructs. Internal reliability is robust, with Cronbach's Alpha (CA) and Composite Reliability (CR) values both exceeding 0.70 (Hair & Alamer, 2022; Hair et al., 2020). Additionally, all constructs' Average Variance Extracted (AVE) values are above 0.50, indicating minimal systematic error and strong item correlations (Hair et al., 2020; Henseler et al., 2016).

Table 2: **Items Reliability, Construct's Reliability and Convergent Validity**

Constructs	Items	Outer Loadings	Cronbach's Alpha	Composite Reliability/CR (rho_c)	Average Variance Extracted (AVE)
Attitude toward use (ATT)	I think ChatGPT can perform the role of tourism recommender for me.	0.86	0.90	0.93	0.77
	Using ChatGPT as a tourism recommender, I can get recommendations everywhere I want.	0.90			
	I am pleased with ChatGPT's ability to provide me with tourism recommendations.	0.89			
	I will further explore ChatGPT's ability to perform the role of tourism recommender.	0.85			
Perceived Enjoyment (ENJ)	It is fun using ChatGPT to get tourism recommendations.	0.88	0.94	0.95	0.80
	I enjoy chatting with ChatGPT to get tourism recommendations.	0.89			
	Using ChatGPT as a tourism recommender has provided me with some amusement.	0.90			
	My free time is fun because I can use it to chat with ChatGPT for tourism recommendations.	0.90			
	Using ChatGPT for tourism recommendations is not boring at all.	0.90			

Constructs	Items	Outer Loadings	Cronbach's Alpha	Composite Reliability/CR (rho_c)	Average Variance Extracted (AVE)
Perceived Ease of Use (EOU)	The menu on ChatGPT is simple and easy to understand.	0.82	0.91	0.93	0.73
	ChatGPT allows me to use it in my preferred language.	0.83			
	ChatGPT is easy as a tourism recommender, just like chatting with a friend.	0.87			
	The more I use ChatGPT for tourism recommendations, the easier I get the information I need.	0.89			
	The more I use ChatGPT for tourism recommendations, the faster I get the necessary information.	0.87			
Trustworthiness (TRU)	Trustworthy information is crucial for me.	0.71	0.89	0.91	0.64
	I know that ChatGPT's recommendations are based on trustworthy references/sources.	0.81			
	The recommendations provided by ChatGPT are trustworthy.	0.86			
	The recommendations provided by ChatGPT are of good quality.	0.82			
	ChatGPT has been trained well to provide trustworthy recommendations.	0.80			
	I am not worried about travelling based on the recommendations provided by ChatGPT.	0.81			
Perceived Usefulness (USE)	ChatGPT recommended me good places to buy souvenirs.	0.74	0.85	0.90	0.69
	ChatGPT can design me a good tour itinerary.	0.83			
	The speed at which ChatGPT provides tourism recommendations has saved me much time.	0.88			
	The ability of ChatGPT to provide me with free-of-charge tourism recommendations has benefited me financially.	0.88			

This study employs the TAM, thus raising concerns about potential discriminant validity issues due to the difficulty respondents may have in differentiating some constructs (Henseler et al., 2015). To address this, the more moderate Fornell-Larcker criterion is used instead of HTMT to assess discriminant validity. Table 3 shows that the highest values in each column exceed those of other values within both columns and rows, confirming that all constructs measure distinct concepts (Hair & Alamer, 2022; Henseler et al., 2015), thereby establishing discriminant validity.

Table 3: **Discriminant Validity Using Fornell-Larcker Criterion**

Constructs	ATT	ENJ	EOU	TRU	USE
ATT	**0.877**				
ENJ	0.790	**0.893**			
EOU	0.723	0.752	**0.856**		
TRU	0.786	0.712	0.680	**0.802**	
USE	0.801	0.837	0.799	0.748	**0.833**

2.3. Structural Model Assessment

The structural model was assessed using the guidelines provided by Hair & Alamer (2022). The first step involved evaluating collinearity, with a VIF value higher than 5.0 indicating potential issues. In this research, the inner VIF values shown in Table 1 ranged from 1.9 to 4.7, suggesting no significant collinearity among constructs. A bootstrap with 10,000 iterations and a one-tailed test at a 5% significance level was used to compute the path coefficients. Results are presented in Tables 4 and 5.

Table 4: **Direct Effect Hypothesis Testing**

Hypo	Path	Std. beta	Std. error	*t*-value	*p*-value	f^2	Supported
1	ENJ → ATT	0.272	0.087	1.408	0.002	0.079	Yes
2	EOU → ATT	0.086	0.083	0.343	0.301	0.010	No
3	EOU → USE	0.539	0.064	2.891	0.000	0.551	Yes
4	TRU → ATT	0.354	0.067	2.131	0.000	0.202	Yes
5	TRU → USE	0.382	0.067	2.242	0.000	0.276	Yes
6	USE → ATT	0.239	0.093	1.000	0.010	0.048	Yes

The hypothesis testing indicates that Generation Z's attitude (ATT) toward using ChatGPT as a Tourism Recommender System was positively influenced by the Perceived Enjoyment they felt when using ChatGPT for tourism recommendation (ENJ) ($\beta = 0.272$, $p < 0.05$), Trustworthiness (TRU) of the recommendation provided by the ChatGPT ($\beta = 0.354$, $p < 0.05$), and the Perceived Usefulness (USE) of ChatGPT in providing tourism recommendation for them ($\beta = 0.239$, $p < 0.05$), thus supporting Hypotheses 1, 4, and 6. Additionally, The Perceived Usefulness (USE) was influenced by the Perceived Ease of Use (EOU) felt by Generation Z when using ChatGPT to get tourism recommendations ($\beta = 0.539$, $p < 0.05$) and their Trust (TRU) toward the recommendation provided by ChatGPT ($\beta = 0.382$, $p < 0.05$), supporting Hypotheses 3 and 5. Notably, the expected influence of Perceived Ease of Use (EOU) on Generation Z's attitude (ATT) to use ChatGPT for tourism recommendation was not supported ($\beta = 0.086$, $p > 0.05$), indicating that Hypothesis 2 is not supported.

Table 5: **Mediation Effect Hypothesis Testing**

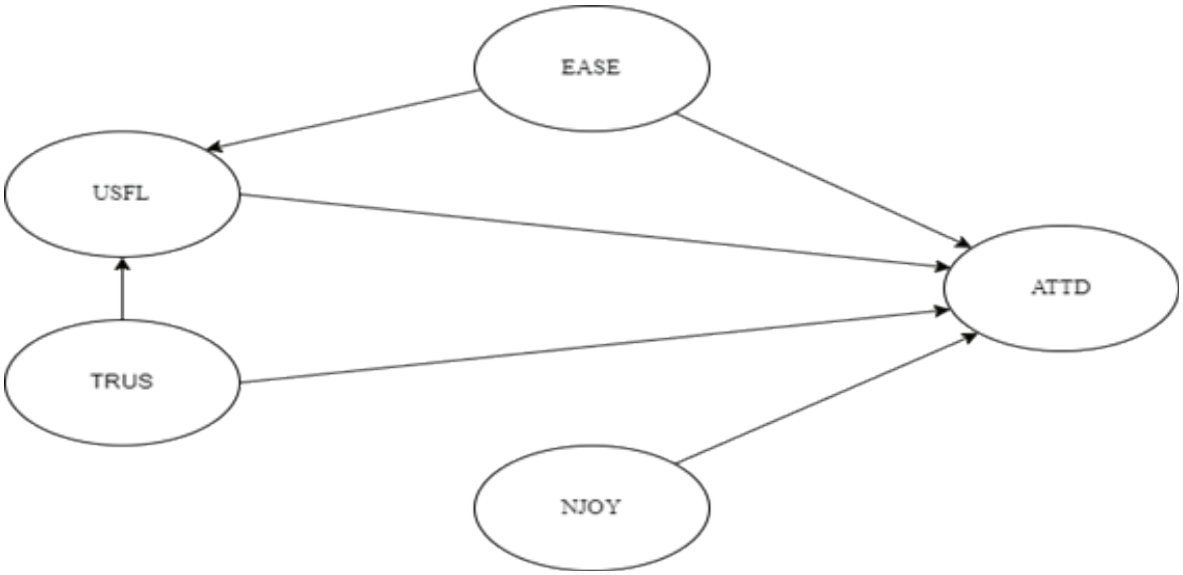
Hypo	Path	Std. beta	*t*-value	*p*-value	Supported
H7	EOU → USE → ATT	0.129	2.427	0.015	Yes
H8	TRU → USE →ATT	0.091	2.342	0.019	Yes

The mediation effect testing indicates that hypotheses 7 and 8 are supported. The easiness of ChatGPT to get recommendations (EOU) indirectly influences Generation Z's attitude (ATT) toward the use of ChatGPT through Perceived Usefulness (USE) ($\beta = 0.129$, $p < 0.05$). Additionally, their trust (TRU) toward the tourism recommendation provided by ChatGPT also indirectly influences their attitude to use (ATT) ChatGPT via Perceived Usefulness (USE) ($\beta = 0.091$, $p < 0.05$).

The model's predictive power was assessed using R^2, and the results are presented in Figure 1. The R^2 value for ATT is 0.748, indicating that EOU, USE, TRU, and ENJ explain 74.8% of the variation in ATT, suggesting that 25.2% of Generation Z's attitude towards using ChatGPT as a tourism recommender system is influenced by other variables. Additionally, The R^2 for USE is 0.716, meaning that the ease of ChatGPT usage (EOU) and the Trustworthiness (TRU) toward the recommendations it provided explains 71.6% of Generation Z's perception of ChatGPT's Usefulness.

The f^2 values as shown in Table 4 were used to determine the effect size for each construct in the study. Cohen (1988) explained that f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively (Kock, 2018). Using Cohen's guideline of f^2 value interpretation, the result shows that ENJ, EOU, and USE have small effects on ATT, while TRU have a medium effect on ATT. Conversely, the effects of EOU and TRU on USE are large and medium, respectively.

Figure 1: **Result of Structural Model Assessment**



2.4. PLSpredict

The predictive power of the model was assessed using Q^2 and PLSpredict. The analysis shows that all Q^2 values are positive, indicating high predictive power (Shmueli et al., 2019). However, the difference between RMSE and MAE values on PLS and LM columns presented on the PLS - LM column of Table 6 shows that most RMSE and MAE values are negative, indicating lower PLS-RMSE or PLS-MAE than LM-RMSE or LM-MAE. Guidelines on PLSpredict (Hair & Alamer, 2022) mentioned that if all of the values of RMSE and MAE on the PLS-LM column are negative, then the model's predictive power is high. If most or half of the RMSE or MAE values are negative, then the model's predictive power is medium. The model's predictive power is low if most or all the RMSE or MAE values on the PLS-LM column are positive. Based on the guideline, the predictive power of this study is medium. This medium predictive power is satisfactory given that in social science, lower predictive power is acceptable (Danks & Ray, 2019).

Table 6. **Predictive Power of the Model**

Constructs	Q^2	PLS		LM		PLS - LM	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
ATT1	0.483	0.631	0.457	0.695	0.508	-0.063	-0.051
ATT2	0.611	0.533	0.405	0.554	0.417	-0.021	-0.012
ATT4	0.592	0.556	0.426	0.601	0.469	-0.045	-0.043
ATT5	0.506	0.643	0.481	0.651	0.477	-0.008	0.004
USE5	0.404	0.681	0.546	0.661	0.523	0.020	0.024
USE6	0.418	0.710	0.561	0.690	0.537	0.020	0.024
USE7	0.588	0.661	0.498	0.677	0.509	-0.016	-0.011
USE8	0.524	0.680	0.523	0.705	0.505	-0.026	0.017

Note: PLS: Partial Least Square, RMSE: Root Means Square Error, MAE: Mean Absolute Error, LM: Linear model

3. DISCUSSION

This study examines Generation Z's acceptance of ChatGPT as a tourism recommender system, highlighting key factors influencing their attitudes. The findings suggest that Trustworthiness, Perceived Enjoyment and Perceived Usefulness positively influence user attitudes, with Perceived Usefulness being affected by both Trustworthiness and Perceived Ease of Use. These results emphasize the importance of Trustworthiness in adopting ChatGPT for tourism, consistent with previous research by Nemec Rudež (2023), Solomovich & Abraham (2024), and Xu et al. (2024)

The result supports Ng et al. (2021) that Enjoyment positively and significantly influences Attitude. However, compared to Trustworthiness, Enjoyment has a smaller effect size on attitudes, just as found by Melián-González et al. (2021). It is surprising, given Generation Z's preference for enjoyable experiences (Ng et al., 2021). The result shows that while Enjoyment matters, it is less significant than Trustworthiness in influencing attitudes toward ChatGPT, thus confirming that Generation Z is opting for reliable information (Corbisiero et al., 2022; Nemec Rudež, 2023; Robinson & Schänzel, 2019).

The result does not entirely support the TAM, particularly regarding Perceived Ease of Use, which showed no significant impact in predicting acceptance. It may be due to Generation Z's familiarity with various information and communication technologies (Corbisiero et al., 2022; Monaco, 2018) and devices (Ng et al., 2021), reducing the importance of Ease of Use in adopting this technology. Despite this, the model's predictive power is strong enough to inform strategic decisions in the tourism sector.

3.1. Implications

Generation Z is likely to adopt ChatGPT for tourism recommendations, and their acceptance is influenced by Trustworthiness, Perceived Enjoyment and Perceived Usefulness. Regarding theoretical implications, the study has successfully extended the TAM by adding Trustworthiness and Perceived Enjoyment to predict Generation Z's acceptance of ChatGPT as a tourism recommender system. While highlighting the importance of Trustworthiness in enhancing Perceived Usefulness and Generation Z's attitude toward using ChatGPT for their tourism recommendation, the study shows that Perceived Ease of Use is not a significant predictor of Generation Z's acceptance of ChatGPT.

The study highlights two significant practical implications regarding Trustworthiness and Perceived Enjoyment, which are crucial for enhancing ChatGPT's Perceived Usefulness and Ease of Use among Generation Z users. Firstly, this generational cohort is notably cautious about the information they consume, often resorting to multiple sources to verify reliability (Dimitriou & AbouElgheit, 2019; Haddouche & Salomone, 2018; Monaco, 2018). Their multitasking capabilities further empower them to efficiently navigate various information streams (Corbisiero et al., 2022; Corbisiero & Ruspini, 2018; Goh & Baum, 2021; Nemec Rudež, 2023; Robinson & Schänzel, 2019). However, Generation Z also exhibits a preference for speed and instant results when searching for information (Dimitriou & AbouElgheit, 2019; Nemec Rudež, 2023). Therefore, it is essential for ChatGPT to provide direct links to references accompanying its tourism recommendations. This approach not only enhances the reliability and trustworthiness of the information provided but also saves time for Generation Z who would otherwise need to cross-reference multiple sources through different applications or websites. Additionally, developers must ensure that ChatGPT is trained on valid and reliable sources of tourism information to generate high-quality and trustworthy recommendations tailored for Generation Z.

Secondly, to effectively meet the Enjoyment needs of Generation Z in tourism recommendations, it is essential for ChatGPT to present the recommendation in diverse formats beyond just text. This generational cohort exhibits a short attention span (Corbisiero & Ruspini, 2018; Dimitriou & AbouElgheit, 2019; Nemec Rudež, 2023) and a preference for quick access to information, which can diminish their engagement if recommendations are solely text-based. Therefore, incorporating visuals such as pictures and videos is crucial, as Generation Z responds more positively to these formats (Corbisiero et al., 2022; Dimitriou & AbouElgheit, 2019). By enhancing the fun aspect of the application through multimedia presentations, the overall Usefulness and Ease of Use will also be improved, making the recommendations more appealing and accessible to this demographic.

3.2. Limitations and Future Research Suggestions

To the best of the author's knowledge, this is the first study to predict Generation Z's acceptance of ChatGPT as a tourism recommender system. Therefore, it contributes to the growing literature on ChatGPT's usage as a source of tourism information or recommendation and Generation Z's information search behaviour. However, some limitations need to be acknowledged. Even though the sample size is adequate, the number is still considerably small, and the gender proportion of the sample is imbalanced despite reflecting the population's gender proportion. Additionally, knowing that Generation Z is heterogenous in their behaviour (Haddouche & Salomone, 2018; Nemec Rudež, 2023), conducting research in diverse cultural contexts with larger and more representative samples would enhance our understanding of this cohort's tourism information-seeking behaviour, particularly regarding the use of ChatGPT.

Given the super-fast growing popularity of ChatGPT (Dwivedi et al., 2023; Kim et al., 2024), there is a possibility that other generation cohorts are also interested in using ChatGPT to get tourism information or recommendations. Therefore, future research should aim to understand other cohorts' acceptance of ChatGPT.

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Please cite this article as:
Suasapha, A.H. (2025). Will Generation Z Use ChatGPT for Tourism Recommendations? Tourism and Hospitality Management, 31(3), 483-491, https://doi.org/10.20867/thm.31.3.11