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The Travel Trend in The Age of TikTok: How Older Chinese Tourists Choose Their Travel Destination – an Empirical Study Using the UTAUT2 Model

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Abstract

This study explores the influence of the short video platform TikTok on the travel decision-making process of older Chinese tourists, particularly in destination selection. With the widespread popularity of social media and short video content, the older population has gradually become an important segment in the tourism market. Grounded in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), this study investigates the extent to which TikTok shapes and facilitates travel decisions among this population. Through a questionnaire survey and structural equation modeling analysis, the results show that TikTok's performance expectancy, effort expectancy, and hedonic motivation significantly affect the travel decisions of older tourists. At the same time, older tourists are influenced by social influence and habit. However, the study also reveals that facilitating convenience has no significant impact on the behavioral intentions of older tourists, indicating that for older tourists accustomed to using technology, facilitating convenience are not decisive factors. This study enriches the application of short video platforms in the travel decision-making of the older, especially the marketing potential of the emerging TikTok platform. The findings provide practical guidance for tourism marketers to better utilize short video platforms to attract older tourists and influence their travel decisions.

Keywords: tourists decision making, destination choice, TikTok, older tourists

1. Introduction

The distinctive feature of social media lies in its accessibility, global reach, and vast information volume (Shu et al., 2020). People tend to prioritize social media as a tool for travel decision-making when planning their trips (Liu et al., 2020). It serves as a key medium for distributing travel-related information and shaping tourist decision-making. Several factors influence consumer travel decisions, such as destination selection, accommodation booking, duration of stay, and specific travel activity arrangements. Many scholars have studied the factors that affect travel decisions. Shin et al. (2022) explores the factors that affect travel decisions during and after the COVID-19 pandemic by applying a framework that combines trust, travel constraints, and the extended theory of planned behavior. Pop et al. (2022) investigates the influence of trust in social media influencers (SMIs) on consumer behavior within the tourism sector, emphasizing its role in fostering and sustaining long-term relationships between businesses and consumers. Consequently, travel information is a crucial determinant in consumer travel choices. For the majority of tourists, the quality of the subsequent experience for tourists largely depends on their initial choice of travel destination(Smallman & Moore, 2010). Tourists evaluate the information they have collected to make their destination choice.

Social media has profoundly shaped content distribution and the development of social values (Yang et al., 2023). In recent years, the rapid expansion of Chinese social media has garnered significant international attention. Currently, short video social platforms like Chinese TikTok and Kuaishou have become popular social media platforms following Weibo and WeChat, with significant social effects that increasingly impact content dissemination, social value transmission, and influence audience media choices and behavioral habits (Yu et al., 2023). Since its launch in September 2016, Chinese TikTok has rapidly emerged as the dominant short video platform, exerting a substantial impact on the tourism industry in recent years. Compared to traditional text-image-based travel information dissemination, Chinese TikTok presents rich travel content in a lightweight, dynamic, and intuitive manner, becoming a new tool for destination marketing and injecting new momentum into the tourism market.

In the tourism sector, short videos play a crucial role in shaping destination perceptions while serving as an effective tool for promotion and marketing. Chinese TikTok currently has over 470 million users, many of whom are older users with a clear interest in travel. With the rise of short video content, more and more older people are using short videos as an important means to plan their travel and vacations. By watching and sharing short videos, older adults can learn about destination information, stimulate their interest in travel, and ultimately make decisions about where to go. The format of short videos is particularly suitable for older people to obtain information because it combines visual and auditory effects, clearly and vividly presenting the characteristics of travel destinations (Gan et al., 2023). Although older adults have lower interest and engagement with Chinese TikTok compared to younger people, as the platform's content becomes more diverse and the user base more varied, older users' activity and sense of participation have gradually increased, especially when seeking travel inspiration and making travel decisions. While the penetration rate of short video consumption among older adults is lower than that of younger people, their influence on the platform, particularly in the areas of health, leisure, and cultural tourism, is gradually increasing. Therefore, Chinese TikTok not only provides a channel for older people to obtain travel information but also introduces a new source of influence on their travel decisions (Z. Wang et al., 2022). The elderly population has gradually become an important and increasingly influential segment in the tourism market.

The emergence of short video platforms has significantly changed tourists' decision-making behavior, as these platforms overlap heavily with the tourism market. They affect the decision-making process in three stages: first, identifying travel needs, second, searching for travel information, and third, making travel decisions. Chinese TikTok and Kuaishou use short videos, live streams, and other diversified methods to stimulate tourists' interest and needs, encouraging them to make final decisions. Meanwhile, short videos offer an innovative approach to presenting destination landscapes and attractions. Unlike other social media formats, they provide greater flexibility and accessibility for a broad user base. Leveraging algorithmic recommendations, Chinese TikTok identifies user preferences and delivers tailored content, shaping the videos users encounter. This targeted distribution model serves as an effective tool for highlighting destination scenery and providing valuable information to prospective travelers (Cao et al., 2023).

Research on tourism has explored the impact of social media on travel decision-making, including the role of advertising (Chu et al., 2020) and trust in influencing travel choices (Pop et al., 2022). While much of the existing literature focuses on travel-oriented platforms such as TripAdvisor (Nilashi et al., 2021) and Airbnb (Tamilmani et al., 2022), the influencing factors of general social media platforms remain insufficiently studied. Compared to other social media formats, short video platforms like Chinese TikTok provide tourists with more immersive and dynamic content through visual storytelling, surpassing the informational depth of text and static images (Liu et al., 2020). In China, Chinese TikTok has played a significant role in boosting the popularity of specific tourist destinations, highlighting its potential to translate online engagement into actual travel experiences. A significant number of users, key opinion leaders in short videos, and tourism-related government departments use Chinese TikTok to share travel-related content. Nearly 70% of users say they enjoy watching city or travel-related short videos on Chinese TikTok, and over 80% of users indicate they are likely to visit offline locations featured in these videos. Therefore, this study explores the critical role of social media in tourism decision-making.

Subsequent research has applied the Technology Acceptance Model (TAM) to investigate the impact of Chinese TikTok on users' travel intentions (C. Wang et al., 2022), although the range of variables explored remains narrow. In contrast, this study employs the UTAUT2 framework and concentrates on the pre-trip stage, specifically the consideration phase of the customer journey, to elucidate how TikTok usage affects destination selection behaviors.

2. Theoretical Basis and Research Hypotheses

Social media is an accessible interactive platform utilizing internet technology, enabling people to generate and disseminate content. Social media platforms facilitate contact and communication among diverse groups. Currently, they serve as the primary means through which travelers acquire travel-related information and make decisions (Munar & Jacobsen, 2013). Owing to the characteristics of tourism service production and consumption, consumers encounter challenges in appropriately evaluating a location prior to selection and visitation. In addition, reducing information asymmetry during the travel process helps enhance the utility of the tourist experience (Amaro et al., 2016). In the era of print media, tourists obtained travel information through newspapers, magazines, or travel agencies. However, with the rise of social media, this landscape has been completely transformed, and user-generated content has become an effective way for tourists to gather travel information. Users can explore reviews from seasoned travelers regarding places or activities and engage in discussions on platforms such as TripAdvisor and Facebook. Consequently, visitors have transitioned into active participants in information dissemination rather than remaining passive users, and they may even generate material independently—they are "prosumers" (Varkaris & Neuhofer, 2017).

Enhancing destination information elevates the propensity of prospective tourists to visit a locale. Social media is the most often utilized and reliable resource for destination selection. Tourists are, to some extent, influenced by the travel experiences of other tourists shared on social media regarding a specific destination (Liu et al., 2019).

This study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), which synthesizes eight prior theoretical models, such as the Theory of Reasoned Action and the Theory of Planned Behavior (Venkatesh et al., 2003). The UTAUT model provides a robust framework for employs novel information technology methodologies to analyze and predict consumer behavior. The UTAUT2 model primarily encompasses four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. This study extends the model by introducing three additional constructs: hedonic motivation, price value, and habit, hence broadening its application to consumer behavior. A multitude of academic studies and practical assessments have substantiated the efficacy and relevance of this paradigm (Çalışkan et al., 2023; Sun & Guo, 2022). This study adopts the UTAUT2 model as the theoretical framework to explore how TikTok influences tourists' destination decision-making. Given the inherent flexibility of social media, the variable of price value is excluded from the model.

2.1 Performance Expectancy

Performance expectancy refers to the perceived benefits that consumers expect to gain from using a technology for a particular task. In the UTAUT2 model, it plays a crucial role in shaping tourists' behavioral intentions. In this study, tourists believe that using TikTok significantly influences their destination decision-making process. Research has shown that performance expectancy has a significant impact on tourists' willingness to adopt technology, particularly among those who engage with advanced technological tools (Gupta et al., 2018). During the pre-trip phase, travelers typically search for large amounts of travel information to determine their destination. For non-travel-specific social media, being able to help make travel plans is crucial for tourists' use. Based on this, the subsequent hypothesis is put forward:

H1: Performance expectancy of using TikTok positively influences tourists' intention to use TikTok for destination decision-making.

2.2 Effort Expectancy

Effort expectancy refers to the perceived level of effort required by users to interact with system, and it is considered a key factor influencing the likelihood of adopting information technology (Venkatesh et al., 2003). In the context of this study, effort expectancy reflects the extent to which tourists expect to exert effort when using TikTok to select a destination. A multitude of experts have substantiated the considerable influence of effort expectancy on visitors' behavioral intentions regarding technology use (Cheunkamon et al., 2020; Oh et al., 2009). In today's age of mature internet technology and widespread smartphone use, social media is widely used and easy to operate. When a technology is popular and users are proficient in its use, studies conducted in different contexts have produced diverse findings regarding the significance of the effort required to use a system. Nevertheless, in this study, effort expectancy is considered a crucial predictor variable, and thus the following hypothesis is proposed:

H2: Effort expectancy of using TikTok positively influences tourists' intention to use TikTok for destination decision-making.

2.3 Social Influence

Social influence is defined as the extent to which individuals perceive the significance of using technology based on the influence of their social circle, including friends, family, peers, and other relevant groups (Venkatesh et al., 2003). In consumer contexts, social influence is often considered a strong predictor of the intention to adopt technology, such as tourists' use of Airbnb or the adoption of travel-related information on smartphones. However, certain studies have suggested that social influence may not have a significant impact on behaviors like sharing information on social media platforms, booking low-cost flights online, or using map applications during travel. Some researchers argue that behaviors like online booking and map applications are already widely accepted and used, so social influence may not be a significant motivator for their use. Social influence is particularly relevant in this study because older people may face higher cognitive barriers when encountering new technology and information, as a result, their decision-making is frequently influenced by recommendations and guidance from friends, family, or colleagues. Within the realm of social media, influencers and celebrities can also exert considerable influence on older users. Building on this, the following hypothesis is put forward:

H3: Social influence of using TikTok positively influences tourists' intention to use TikTok for destination decision-making.

2.4 Facilitating Conditions

Facilitating conditions are defined as the resources and support that users believe are accessible when interacting with a system. In the UTAUT2 model, facilitating conditions are considered an influencing factor on both the behavioral intention and use behavior of technology, positively promoting both (Venkatesh et al., 2003). For older tourists, they may face more technological barriers when using smartphones and related apps, such as lower adaptability to new technologies and a lack of experience or support resources. Therefore, older users' behavioral intentions and use behavior may depend more on the support and facilitating conditions provided by the system, such as easy-to-use interfaces, clear instructions, and support from family members or social networks. Facilitating conditions play an important role in older users' acceptance and use of technology, especially when obtaining information through TikTok for travel decision-making. Based on this, the following hypothesis is proposed:

H4: Facilitating conditions perceived in using TikTok positively influence tourists' intention to use TikTok for destination decision-making.

2.5 Hedonic Motivation

Hedonic motivation refers to the pleasure users derive from using a system (Venkatesh et al., 2012). Initially, perceived enjoyment was added to the technology acceptance model to measure inherent motivation related to technology use, serving as one of the predictive variables for different types of behavioral intentions. In some research contexts, perceived enjoyment is considered a weaker predictor than perceived usefulness and perceived ease of use, but when it comes to hedonic systems like social media, perceived enjoyment may have a greater influence. As the UTAUT2 model evolved, hedonic motivation was included and is considered a significant factor in individual intention to use technology. In the tourism context, potential tourists may be more interested in browsing social media content such as photos, reviews, and videos from other travelers rather than focusing on the search results themselves. Based on this, the following hypothesis is proposed:

H5: Hedonic motivation perceived in using TikTok positively influences tourists' intention to use TikTok for destination decision-making.

2.6 Habit

Habit refers to the extent to which users develop a stable preference for a behavior through usage, and in the UTAUT2 model, habit is considered an influencing factor for both behavioral intention and use behavior, positively promoting both. In the process of using internet applications, users can easily become addicted, which further strengthens their use behavior. Empirical studies have shown that habit significantly influences both behavioral intention and use behavior. In tourism contexts, users often create habitual behaviors like sharing travel experiences on social media or using smartphone apps for trip planning. Thus, habit may also affect the way older users interact with TikTok in their destination decision-making process. Based on this, the following hypothesis is proposed:

H6: Habit of using TikTok positively influences tourists' intention to use TikTok for destination decision-making.

2.7 Behavioral Intention and Use Behavior

Behavioral intention refers to tourists' intention or tendency to use TikTok when selecting a travel destination. In this study, it specifically refers to the concrete behavioral intention exhibited by tourists when using TikTok to choose their destination. According to the UTAUT2 model, behavioral intention is considered an important precursor to use behavior (Venkatesh et al., 2012). Numerous scholars have conducted empirical studies on the relationship between behavioral intention and use behavior (Venkatesh et al., 2003; Zhou et al., 2023). Based on this theoretical foundation, the following hypothesis is proposed:

H7: Behavioral intention has a positive effect on tourists' TikTok use behavior to select destinations.

3. Empirical Research

3.1 Questionnaire Design

The questionnaire in this study consists of three main sections: (i) four items related to respondents' use of TikTok; (ii) respondents' demographic characteristics; and (iii) eight variables relevant to this study. A five-point Likert scale was employed to collect respondents' data. The questionnaire was adapted based on practical considerations and existing validated scales from previous scholarly research. Appendix A presents the specific details of the eight variables examined in this study.

The questionnaire was initially developed in English; however, since the respondents of this study are Chinese, it was necessary to translate it into Chinese. To ensure the accuracy of the content, two senior experts proficient in English and specializing in the field of tourism studies were invited to review and verify the translation. After finalizing the questionnaire, a pre-test was conducted with 10 participants. Feedback from this pre-test led to revisions of any unclear or potentially confusing sections to ensure that participants could comprehend the content fully, thereby enhancing the test's quality. To ensure the reliability and validity of the questionnaire, this study conducted a pilot test by collecting 30 survey responses in Handan. According to the reliability standards outlined by Nunnally and Bernstein (1994), the Cronbach's alpha values from the pilot test were above 0.7, indicates that the questionnaire demonstrates good reliability and validity.

3.2 Sample Selection and Data Collection

To ensure the broad representativeness of the questionnaire results, a combination of online and offline distribution methods was used. Data collection began in March 2024 and lasted for 4 weeks. The online questionnaire was distributed through the Wenjuanxing platform and used a snowball sampling method, with further distribution through social media platforms such as WeChat, avoiding limited distribution to groups like the distributors, thus enhancing sample diversity. The first question in the questionnaire included a screening function to ensure that respondents had experience using TikTok. At the same time, offline questionnaires were distributed through random sampling to reduce bias and better reflect the actual situation. Handan, Hebei Province, was selected as the survey location, as the city is considered highly representative. By the final week of March 2024, total of 511 valid questionnaires were collected (200 offline and 311 online). The final sample data were used for statistical analysis.

4. Data Analysis: Results and Discussion

4.1 Descriptive Statistics

41.1% of respondents indicated that they have been using TikTok for more than two years. The daily usage time of respondents was generally consistent, with more than half using TikTok for over 1 hour per day. Additionally, 59.3% of respondents stated that they use the platform for travel-related activities (Table 1). Over fifty percent of the respondents indicated that viewing high-quality travel videos influenced their decision to visit a destination. Many respondents stated that they would consider visiting a destination after seeing an attractive travel video. This shows that TikTok has become popular in China and is playing an increasingly important role in the tourism industry by promoting tourist destinations as a leisure and entertainment social platform. Particularly, for older tourists, TikTok has become an important reference platform when choosing travel destinations.

Table 1. Respondents' profile and use of TikTok

Characteristic	Items	Frequency	Percentage
Gender	Male	267	52.3%
	Female	244	47.7%
Work experience	Professional	74	14.5%
	Management	53	10.4%
	Agriculture	47	9.2%
	Employee	72	14.1%
	Business, service personnel	64	12.5%
	Unemployed	37	7.2%
	Former employee or retired employee	89	17.4%
	Other	75	14.7%
Education Level	≤Diploma/Bachelor	48	44.8%
	Diploma/Bachelor	142	41.9%
	Master	136	11.0%
	Doctoral	12	2.3%
Use TikTok Time	Under 6 months	32	6.3%
	6 months to 1 year	79	15.5%
	1 year to 2 years	190	37.2%
	>2 years	210	41.1%
Average daily usage	Under 30 min	47	9.2%
	30 min to 1 h	83	16.2%
	1 h to 2 h	226	44.2%
	>2 h	155	30.3%
Using TikTok for travel purposes	Yes	303	59.3%
	No	208	40.7%
Drawn to a destination by a brief travel video	Not	25	4.9%
	Probably not	98	19.2%
	Maybe	120	23.5%
	Probably	216	42.3%
	Definitely	62	12.1%

4.2 Reliability and Validity Analysis

This study utilized SmartPLS 4.0 software for data analysis. The first step involved evaluating the reliability and validity of the model. The reliability indicators are mostly utilized to assess the consistency and dependability of the questionnaire survey. reliability is measured using Cronbach's α coefficient and Composite Reliability (CR). According to prior research, both Cronbach's α and Composite Reliability values should exceed 0.7 for satisfactory reliability.

The data analysis results (Table 2) indicate that the Cronbach's α values for the latent variables in this study range from 0.784 to 0.851, all exceeding the acceptable threshold. The Composite Reliability (CR) scores span from 0.785 to 0.852 and from 0.874 to 0.907, all exceeding 0.7. This signifies that the model's internal consistency and stability are satisfactory, thus passing the reliability assessment and permitting progression to the subsequent testing phase.

The evaluation of the model's convergent and discriminant validity is often grounded in the Average Variance Extracted (AVE). When the AVE exceeds 0.5, it signifies that over half of the questionnaire questions may be elucidated by the latent variable. The factor loadings for each item must be at least 0.5. A factor loading exceeding 0.5 signifies that the item effectively elucidates the hidden variable it assesses. If both requirements are satisfied, it indicates that the model's convergent validity is adequate. The AVE values for the latent variables in this investigation range from 0.666 to 0.764, all surpassing the 0.5 barrier. The factor loadings for each item exceed 0.5, signifying that the model demonstrates strong convergent (or construct) validity.

Table 2. Reliability and validity testing

Variable	Item Factor	Loading	Cronbach's α	CR (rho_a)	CR (rho_c)	AVE
BI	BI1	0.816	0.784	0.785	0.874	0.698
	BI2	0.868				
	BI3	0.822				
EE	EE1	0.781	0.835	0.836	0.890	0.669
	EE2	0.815				
	EE3	0.828				
	EE4	0.846				
FC	FC1	0.836	0.833	0.834	0.889	0.666
	FC2	0.797				
	FC3	0.801				
	FC4	0.829				
HA	HA1	0.867	0.851	0.852	0.900	0.692
	HA2	0.823				
	HA3	0.857				
	HA4	0.778				
HM	HM1	0.844	0.814	0.815	0.890	0.729
	HM2	0.869				
	HM3	0.848				
PE	PE1	0.797	0.842	0.848	0.895	0.680
	PE2	0.790				
	PE3	0.897				
	PE4	0.811				
SI	SI1	0.866	0.846	0.847	0.907	0.764
	SI2	0.883				
	SI3	0.874				
UB	UB1	0.864	0.834	0.835	0.900	0.751
	UB2	0.860				
	UB3	0.876				

Discriminant validity assesses the extent of distinction among various factors within the scale. It assesses the clarity with which observable variables may be differentiated among several latent variables. This study uses cross-loadings and the Fornell-Larcker criterion to assess discriminant validity.

The cross-loadings test indicates the extent to which an observable variable contributes to its associated latent variable. The evaluation criterion stipulates that the loading of an observable variable on its corresponding latent variable must be significantly greater than its loadings on other latent variables in the model. Upon fulfillment of this criteria, the test is deemed successful, signifying robust discriminant validity.

According to the Fornell-Larcker criterion, the assessment standard dictates that the square root of the Average Variance Extracted (AVE) for each latent variable must exceed the absolute values of the correlation coefficients between that latent variable and other latent variables within the model. Furthermore, the HTMT (Heterotrait-Monotrait Ratio) values for each latent variable must be below 0.9. Meeting all three criteria signifies that the developed model possesses strong discriminant validity.

The analysis indicates that the cross-loadings for all observable variables are markedly greater for their corresponding latent variables compared to other latent variables in the model, as illustrated in Table 3 below.

Table 3. Factor loading coefficients between variables

	BI	EE	FC	HA	HM	PE	SI	UB
BI1	**0.816**	0.444	0.317	0.464	0.452	0.394	0.433	0.459
BI2	**0.868**	0.462	0.303	0.472	0.470	0.460	0.480	**0.504**
BI3	**0.822**	0.451	0.282	0.477	0.469	0.443	0.418	**0.521**
EE1	0.424	**0.781**	0.259	0.334	0.322	0.358	0.319	0.380
EE2	0.454	**0.815**	0.217	0.323	0.392	0.324	0.361	0.424
EE3	0.433	**0.828**	0.271	0.339	0.313	0.305	0.363	0.394
EE4	0.459	**0.846**	0.244	0.331	0.347	0.388	0.358	0.412
FC1	0.309	0.271	**0.836**	0.414	0.252	0.287	0.270	0.266
FC2	0.289	0.240	**0.797**	0.338	0.185	0.265	0.260	0.249
FC3	0.280	0.243	**0.801**	0.407	0.214	0.265	0.267	0.225
FC4	0.292	0.230	**0.829**	0.370	0.211	0.327	0.281	0.230
HA1	0.484	0.362	0.405	**0.867**	0.357	0.347	0.373	0.384
HA2	0.474	0.328	0.368	**0.823**	0.326	0.318	0.318	0.359
HA3	0.462	0.331	0.400	**0.857**	0.304	0.354	0.378	0.404
HA4	0.455	0.327	0.386	**0.778**	0.330	0.352	0.328	0.365
HM1	0.462	0.356	0.265	0.350	**0.844**	0.406	0.353	0.384
HM2	0.486	0.373	0.193	0.348	**0.869**	0.441	0.342	0.426
HM3	0.474	0.348	0.222	0.317	**0.848**	0.383	0.323	0.382
PE1	0.402	0.309	0.321	0.296	0.363	**0.797**	0.369	0.359
PE2	0.385	0.320	0.293	0.334	0.381	**0.790**	0.314	0.323
PE3	0.448	0.348	0.286	0.340	0.449	**0.897**	0.351	0.395
PE4	0.466	0.402	0.263	0.383	0.387	**0.811**	0.424	0.423
SI1	0.448	0.377	0.297	0.365	0.328	0.398	**0.866**	0.341
SI2	0.482	0.382	0.286	0.348	0.381	0.410	**0.883**	0.351
SI3	0.462	0.365	0.283	0.389	0.331	0.358	**0.874**	0.342
UB1	**0.513**	0.426	0.263	0.374	0.407	0.406	0.333	**0.864**
UB2	**0.502**	0.402	0.245	0.411	0.389	0.377	0.343	**0.860**
UB3	**0.526**	0.451	0.265	0.397	0.414	0.406	0.350	**0.876**

The square root of the Average Variance Extracted (AVE) for each variable is greater than the correlation coefficients between any two variables, as shown in Table 4.

Table 4. Correlation coefficient between variables

	BI	EE	FC	HA	HM	PE	SI	UB
BI	0.836							
EE	0.541	0.818						
FC	0.359	0.302	0.816					
HA	0.564	0.405	0.469	0.832				
HM	0.555	0.421	0.265	0.396	0.854			
PE	0.518	0.421	0.351	0.412	0.480	0.825		
SI	0.531	0.429	0.330	0.420	0.397	0.445	0.874	
UB	0.593	0.492	0.297	0.455	0.466	0.458	0.394	0.867

Note: Diagonal values represent the square root of the AVE, while off-diagonal values indicate the correlation coefficients between variables.

The HTMT values for all latent variables are less than 0.9, as shown in Table 5.

Table 5. Heterotrait-Monotrait Test Results

	BI	EE	FC	HA	HM	PE	SI	UB
BI								
EE	0.669							
FC	0.445	0.363						
HA	0.690	0.481	0.557					
HM	0.695	0.509	0.321	0.476				
PE	0.634	0.499	0.421	0.485	0.579			
SI	0.652	0.510	0.394	0.496	0.478	0.524		
UB	0.732	0.589	0.356	0.540	0.565	0.542	0.469	

4.3 Structural Equation Model Testing

Based on the results of the reliability and validity analyses above, the model in this study demonstrates good reliability and validity, allowing for further structural equation model testing.

4.3.1 Multicollinearity Analysis

Before hypothesis testing, a multicollinearity analysis must be conducted to ensure that no potential multicollinearity issues exist within the model. The indicator used to measure this is the Variance Inflation Factor (VIF). According to Hair, a VIF value less than or equal to 5 indicates that there are no multicollinearity issues between variables. SmartPLS 4.0 was used to calculate the VIF values directly.

The findings indicate that the VIF values for the latent variables in this study's model vary from 1.000 to 1.573, all below 5, signifying the absence of multicollinearity issues among the latent variables in the model, as presented in Table 6.

Table 6. Latent variable VIF test results

Latent variables	BI	UB
BI		1.000
EE	1.452	
FC	1.354	
HA	1.573	
HM	1.481	
PE	1.568	
SI	1.478	

The VIF values of the observed variables in the model range from 1.558 to 2.751, all of which are below 5, indicating that there are no multicollinearity issues among the observed variables, as shown in the Table 7 below.

Table 7. Observed variable VIF test results

Observed variables	VIF	Observed variables	VIF
BI1	1.607	HM1	1.758
BI2	1.855	HM2	1.901
BI3	1.558	HM3	1.748
EE1	1.616	PE1	1.764
EE2	1.751	PE2	1.851
EE3	1.933	PE3	2.751
EE4	2.020	PE4	1.744
FC1	1.891	SI1	1.986
FC2	1.698	SI2	2.076
FC3	1.753	SI3	2.042
FC4	1.885	UB1	1.908
HA1	2.355	UB2	1.902
HA2	1.845	UB3	1.995
HA3	2.308		
HA4	1.601		

4.3.2 Analysis of Model's Explanatory Power

To assess the explanatory power of the model, this study first examines the coefficient of determination (R^2) of the endogenous latent variables. The coefficient of determination is calculated as the square of the correlation between the actual and predicted values of a specific endogenous latent variable, reflecting the extent to which the variance of these variables can be explained by exogenous latent variables. This measure is commonly used to evaluate the explanatory power of exogenous variables in the structural model and is one of the most prevalent indicators for assessing model quality. According to Chin, an R^2 value of $\geqslant 0.67$ suggests strong explanatory power, $0.33 \leqslant R^2 < 0.67$ indicates moderate explanatory power, $0.19 \leqslant R^2 < 0.33$ suggests weak explanatory power, and $R^2 < 0.19$ implies very weak explanatory power. Cohen, in his research on user behavior, proposes that an R^2 value greater than 0.13 indicates good explanatory power. The coefficient of determination for BI is 0.551, exceeding 0.33, which reflects moderate explanatory power. Similarly, the coefficient of determination for AB is 0.352, also greater than 0.33, indicating moderate explanatory power (Table 8). Overall, the research model in this study demonstrates effective explanatory power.

Table 8. Latent variable determination coefficient R^2 result

Endogenous variables	R-square	Explanation ability
BI	0.551	Moderate
UB	0.352	Moderate

Secondly, this study examines the effect size (f^2) to assess the influence of exogenous variables on endogenous variables. The effect size, f^2, represents the change in R^2 when a specific exogenous latent variable is removed from the model. It is used to evaluate whether the explanatory power of an independent variable on a dependent variable is adequate. According to Cohen's criteria, an f^2 value greater than 0.02 indicates effective utility: $0.02 \leq f^2 \leq 0.15$ suggests a small effect of the independent variable on the dependent variable; $0.15 \leq f^2 \leq 0.35$ indicates a medium effect; and $f^2 \geq 0.35$ signifies a large effect.

As shown in Table 9, except for FC's lack of influence on BI, the effects (f^2) of other exogenous variables on endogenous variables are within an acceptable range.

Table 9. Latent variable explanation effect f^2 results

	BI	UB
BI		0.542
EE	0.064	
FC	0.000	
HA	0.091	
HM	0.079	
PE	0.025	
SI	0.051	

4.3.3 Model Predictive Power Analysis

The predictive power of the model refers to its ability to accurately predict the values of endogenous latent variables. The Q^2 value is an effective measure for evaluating a model's predictive capability. A Q^2 value greater than 0 indicates that the model has predictive power for the endogenous latent variables, otherwise, it lacks predictive power.

In this study, the Q^2 values for all endogenous latent variables are greater than 0, indicating that the exogenous variables possess a certain degree of predictive power for the endogenous variables. Details are provided in Table 10.

Table 10 Endogenous latent variable Q^2 table

Endogenous variables	Q^2predict
BI	0.534
UB	0.346

4.3.4 Direct Effect Testing

This study employs the Bootstrapping method in SmartPLS 4.0 to test the hypotheses, with 5,000 resamples. The path coefficient significance is determined based on whether the 95% confidence interval excludes zero. If the path coefficient is significant, the hypothesis is supported.

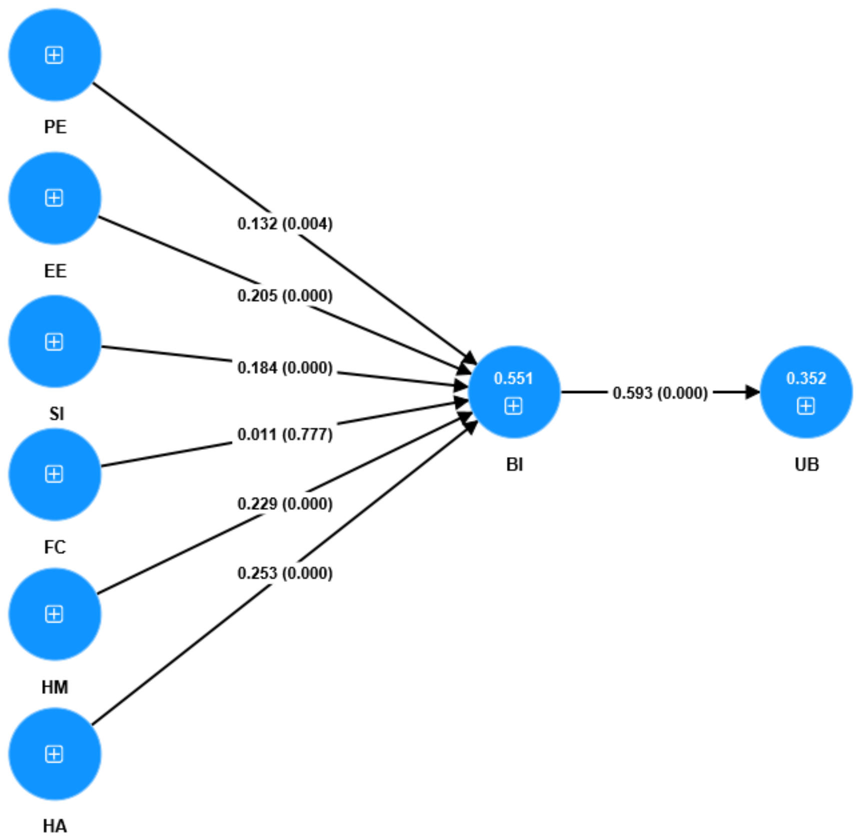

Fig. 1. Direct effect and mediation effect test

As can be seen from the Fig1, the hypothesis testing results for the model are summarized in Table 11. Key findings are as follows: The path coefficient from BI to UB is 0.593 (T = 17.339, P = 0.0, and confidence interval [0.522, 0.657], excluding 0), indicating a significant positive impact of BI on UB. This implies that higher BI leads to higher UB. The path coefficient from EE to BI is 0.205 (T = 4.618, P = 0.0, and confidence interval [0.12, 0.293], excluding 0), demonstrating a significant positive effect of EE on BI. This means that greater EE leads to higher BI. The path coefficient from FC to BI is 0.011 (T = 0.284, P = 0.777, and confidence interval [-0.063, 0.086], including 0), indicating that FC does not significantly affect BI. The path coefficient from HA to BI is 0.253 (T = 5.714, P = 0.0, and confidence interval [0.16, 0.336], excluding 0), showing that HA has a significant positive impact on BI. This implies that higher HA leads to higher BI. The path coefficient from HM to BI is 0.229 (T = 5.395, P = 0.0, and confidence interval [0.148, 0.316], excluding 0), indicating a significant positive effect of HM on BI. This means that greater HM leads to higher BI. The path coefficient from PE to BI is 0.132 (T = 2.92, P = 0.004, and confidence interval [0.043, 0.221], excluding 0), demonstrating that PE significantly and positively influences BI. Higher PE leads to higher BI. The path coefficient from SI to BI is 0.184 (T = 4.89, P = 0.0, and confidence interval [0.11, 0.258], excluding 0), indicating a significant positive effect of SI on BI. This suggests that higher SI leads to higher BI. Detailed results are provided in Table 11.

Table 11. Direct effect test results

Path	Path coefficient	T	P	95%CI	
BI→UB	0.593	17.339	0.000	0.522	0.657
EE→BI	0.205	4.618	0.000	0.120	0.293
FC→BI	0.011	0.284	0.777	-0.063	0.086
HA→BI	0.253	5.714	0.000	0.160	0.336
HM→BI	0.229	5.395	0.000	0.148	0.316
PE→BI	0.132	2.920	0.004	0.043	0.221
SI→BI	0.184	4.890	0.000	0.110	0.258

5. Mediation Effect Testing

This study employs the Bootstrapping method to analyze mediation effects. The Bootstrapping method involves repeatedly sampling from the population to create samples that serve as substitutes for the population. In this context, the Bootstrapping population is the original sample, and the resampled datasets, with replacement, closely resemble the original sample. SmartPLS 4.0 provides the p-values and 95% confidence intervals directly in its output, enabling the assessment of mediation effects by determining whether these values fall within the threshold range.

The results of the Bootstrap test indicate the following: For the path HM→BI→UB, the mediation effect value is 0.136 (T = 4.978, P = 0.0, and confidence interval [0.085, 0.192], excluding 0). This demonstrates that BI plays a significant mediating role in the relationship between HM and UB. For the path FC→BI→UB, the mediation effect value is 0.006 (T = 0.283, P = 0.777, and confidence interval [-0.037, 0.052], including 0). This indicates that BI does not significantly mediate the relationship between FC and UB. For the path EE→BI→UB, the mediation effect value is 0.121 (T = 4.435, P = 0.0, and confidence interval [0.071, 0.177], excluding 0). This suggests that BI significantly mediates the relationship between EE and UB. For the path SI→BI→UB, the mediation effect value is 0.109 (T = 4.681, P = 0.0, and confidence interval [0.064, 0.154], excluding 0). This indicates that BI significantly mediates the relationship between SI and UB. For the path HA→BI→UB, the mediation effect value is 0.15 (T = 5.522, P = 0.0, and confidence interval [0.094, 0.203], excluding 0). This demonstrates that BI significantly mediates the relationship between HA and UB. For the path PE→BI→UB, the mediation effect value is 0.078 (T = 2.875, P = 0.004, and confidence interval [0.026, 0.133], excluding 0). This suggests that BI significantly mediates the relationship between PE and UB. Detailed results are provided in Table 12.

Table 12. Results of the mediation effect test

Path	effect value	T	P	95%CI	
HM→BI→UB	0.136	4.978	0.000	0.085	0.192
FC→BI→UB	0.006	0.283	0.777	-0.037	0.052
EE→BI→UB	0.121	4.435	0.000	0.071	0.177
SI→BI→UB	0.109	4.681	0.000	0.064	0.154
HA→BI→UB	0.150	5.522	0.000	0.094	0.203
PE→BI→UB	0.078	2.875	0.004	0.026	0.133

6. Summary and Discussion

This study aimed to examine the factors that influence older tourists' use of TikTok in the destination selection phase of their travel decision-making process. Structural Equation Modelling (SEM) was employed to assess the impact of these factors on behavioral intention (BI) and use behavior (UB). Additionally, the Bootstrapping method was applied to investigate mediation effects. The findings offer a thorough understanding of the key factors involved and highlight the roles of various variables within the decision-making process.

Firstly, our results show that BI has a significant positive impact on UB (path coefficient = 0.593, T = 17.339, P = 0.0), indicating that stronger behavioral intention increases the likelihood of use behavior. This finding aligns with previous research, demonstrating that BI is a key predictor of UB (Ajzen, 1991). Furthermore, we found that factors influencing BI include Effort Expectancy (EE), Habit (HA), Hedonic Motivation (HM), Social Influence (SI), and Performance Expectancy (PE). Among them, EE has a positive impact on BI (path coefficient = 0.205, T = 4.618, P = 0.0), indicating that when users perceive that TikTok reduces the effort required for use, their BI is stronger. Additionally, PE, SI, and HA were also significantly verified to impact BI, with PE influencing BI (path coefficient = 0.132, T = 2.92, P = 0.004), HA influencing BI (path coefficient = 0.253, T = 5.714, P = 0.0), and HM influencing BI (T = 0.229, P = 5.395, P = 0.0). These findings suggest that older tourists' use of TikTok is driven not only by its utility and hedonic motivation but also by external social pressure and habitual use. Secondly, our results indicate that Facilitating Conditions (FC) do not significantly affect BI (path coefficient = 0.011, T = 0.284, P = 0.777). One the one hand, this finding is consistent with some studies suggesting that for users already familiar with technology, the convenience and support provided by the system are no longer decisive factors influencing BI (Venkatesh et al., 2003). We speculate that with the widespread adoption of technology, users' experience and habits may cause excessive system support to have a counterproductive effect, thereby weakening the impact of convenience on BI. On the other hand, this challenges conventional assumptions and highlights the need for a contextualized understanding of FC in short-video platforms. One possible explanation is the increasing digital literacy of older adults. As smartphone penetration rises among senior users in China, many older individuals have become more proficient in using digital tools, reducing their dependency on external support. Unlike in earlier years when technological barriers were more pronounced, older adults today are often comfortable navigating social media platforms like TikTok. This suggests that, rather than relying on formal facilitating conditions such as easy-to-use interfaces or technical support, older users are more likely to learn through trial and error, peer interactions, and habitual engagement with the platform. Additionally, the design and usability of TikTok may contribute to the reduced significance of FC. Unlike complex applications that require significant guidance, TikTok's intuitive user interface and AI-driven content recommendation system simplify engagement, making formal facilitating conditions less critical. The platform's content format-short, visual, and highly interactive-minimizes the cognitive load required for users to explore and navigate the app. In contrast to services such as mobile banking or telehealth, where FC plays a crucial role in adoption, TikTok's entertainment-driven model makes structured support mechanisms less necessary.

In terms of mediation effects, we used the Bootstrapping method for testing. Results show that BI plays a significant mediating role in multiple paths. In the path "HM → BI → UB," the mediation effect of BI is 0.136 (T = 4.978, P = 0.0, and the confidence interval [0.085, 0.192] does not include 0), indicating that BI plays a significant mediating role in the impact of HM on UB. Similarly, BI also plays a significant mediating role in the paths "EE → BI → UB" and "SI → BI → UB," suggesting that BI is a key mechanism through which these factors influence UB. However, although BI plays a mediating role in most paths, it does not mediate the path "FC → BI → UB" (path coefficient = 0.006, T = 0.283, P = 0.777), emphasizing again the weak influence of FC on BI and that the ease of use of technology is no longer a decisive factor for users already familiar with the technology.

Fourth, this study finds that older Chinese tourists primarily rely on TikTok's technological features (performance expectancy, effort expectancy, and hedonic motivation) for travel decision-making, whereas older U.S. tourists are more influenced by age-related social comparisons with travel influencers. Research on U.S. travelers suggests that they prefer destinations promoted by influencers of a similar age, particularly when facing high interpersonal travel constraints (Leung et al., 2025). In contrast, Chinese older tourists focus more on information accessibility and entertainment value rather than influencer relatability.

6.1 Theoretical Contributions

The theoretical contributions of this study are reflected in the following aspects:

Firstly, innovative application of the theoretical model. This study used the UTAUT2 model to explore how BI influences the behavior of older tourists TikTok use. This model has been widely used in technology adoption and consumer behavior studies, but its application in social media, especially for older adults, is rare. This study deepened the application of the UTAUT2 model in the context of tourism decision-making, with a particular focus on its relevance for older adults. While the model has been extensively employed in research on digital technology adoption and behavioral intention (BI), it has received limited attention when applied to the older adult demographic. In our study, we found that for older adults, the facilitating conditions of the TikTok platform (FC) is not the key factor determining their BI. This finding is significant for current research on technology acceptance. Older adults' technology acceptance is more influenced by social influence, habit, and hedonic motivation rather than facilitating conditions. This discovery helps us understand older adults' behavior patterns on digital platforms and provides a new perspective for future research on their behavior.

Secondly, the study shows that there is a significant positive relationship between older adults' BI and UB, and multiple factors such as SI, HM, and HA significantly influence BI. In their tourism decision-making process, older adults are more dependent on suggestions from others and the influence of their social circles. Simultaneously, their habitual use reinforces their BI. These findings enrich intergenerational difference research and provide practical evidence for designing social media platforms suitable for older adults. Moreover, by introducing the dual perspectives of BI and UB, this study not only focused on older adults' BI on TikTok but also examined the realization of their use behavior. This research design offers a new framework and methodology for subsequent studies on older adults' decisions and behaviors on digital platforms.

Finally, the findings provide a theoretical basis for future research in areas such as older adults' digital participation and tourism decision-making and offer strategic recommendations for marketers and platform developers on better serving this demographic.

6.2 Practical Implications

This study reveals the multiple factors influencing older adults' use of TikTok for destination selection and provides valuable practical guidance for tourism marketers and social media platform developers. Through analyzing the use behavior of older adults on TikTok, we can better understand their decision-making process on social media platforms, thereby helping related industries develop more precise marketing strategies.

Firstly, the study found that BI significantly influences older adults' use behavior (UB) of TikTok. This suggests that older adults' acceptance of TikTok is closely related to their BI. Therefore, tourism marketers should focus on strategies to stimulate older adults' BI during promotion, such as enhancing platform usability, providing simple and clear operational guidance, and increasing older users' engagement with the platform. Moreover, the study shows that EE and PE significantly influence older adults' BI, meaning that older adults pay more attention to the benefits brought by technology when choosing travel platforms. DMOs (Destination Marketing Organizations) should address the practical needs of this group, providing suitable technological support and promotional information to encourage participation.

Secondly, hedonic motivation (HM) and habit (HA) have significant impacts on older tourists, which is distinct from younger consumers. Tourism marketers can capitalize on this characteristic by focusing more on emotional and engaging content in their design to capture older adults' interest. Social media platforms can enhance user retention by optimizing user experiences and increasing interactivity, such as setting up social circles suitable for older adults or enabling them to share their travel experiences.

Furthermore, the findings show that facilitating conditions (FC) have a weak influence on BI, especially among older adults. With the popularization of technology and increased familiarity with social platforms among older users, technical convenience is no longer a major factor affecting their BI. Marketers should avoid relying excessively on complex technological features and instead focus on simple and intuitive interfaces and content delivery to meet older users' needs.

Finally, the study highlights the commercial opportunities brought by the growing penetration of short video platforms among older adults. Using platforms like TikTok, tourism businesses can enhance their brand influence among older tourists and expand their market share. Data analysis and market trends provided by this research support more informed and effective marketing strategies.

In summary, social media marketing targeting older adults should focus more on their technological adaptability and emotional needs. By enhancing platform usability, increasing interactivity, and offering personalized incentives, the tourism industry can more effectively attract older tourists and influence their travel decisions. At the same time, social media platforms should consider the specific needs of older users in their designs, providing personalized, easy-to-use experiences to promote their activity and loyalty.

6.3 Limitations and Future Research Directions

This study has certain limitations in the following aspects, which may impact the generalizability and explanatory power of the research findings:

Firstly, the conceptual framework adopted in this study is based on the UTAUT2 theory. However, this model primarily focuses on the relationships between individual factors and behavioral intention and does not fully consider the influence of more individual, internal, or contextual factors. Therefore, future research could further expand the theoretical framework to include more relevant variables, such as individual psychological traits, cultural backgrounds, and changes in the external environment, to enrich the understanding of TikTok use behavior.

Secondly, this study focuses on the Chinese market, selecting China as the research context primarily based on its large tourism market and the popularity of TikTok in the region. Despite China being home to the largest social media user base globally, and TikTok's widespread use both domestically and internationally, the applicability of the findings may be constrained by geographical and cultural variations. Consequently, the results may not be universally relevant to older tourists in other countries or regions. Future studies could explore cross-national comparative analyses to examine the influence of TikTok and similar platforms on travel decision-making among older tourists across different cultural contexts, offering a more comprehensive understanding for global tourism marketing strategies. Finally, this study only considers TikTok as a single social media platform, which may differ significantly from other platforms, such as YouTube and Vimeo. To fully understand the role of social media in tourism decision-making, future research could empirically analyze other popular social media platforms using the same conceptual framework. This approach could compare the influence of different platforms on tourism decision-making and explore how to customize tourism marketing strategies based on the characteristics of each platform. By doing so, more diverse research findings could be obtained, providing broader and more targeted practical guidance for the tourism industry.

Appendix A

Measurement Items	
Performance expectancy (Venkatesh et al., 2003)	
PE1	I find the system useful for my work
PE2	Using this system allows me to get things done faster
PE3	Using this system increases my productivity
PE4	I would increase my chances of getting a raise if I used the system
Effort expectancy (Venkatesh et al., 2003)	
EE1	My interactions with the system are clear and easy to understand
EE2	It was easy for me to become proficient in using the system
EE3	I found the system easy to use
EE4	It was easy for me to learn to operate the system
Social influence (Wang & Shih, 2009)	
SI1	If individuals within my social circle (such as family, friends, and peers) use TikTok to explore travel-related content, I am likely to be motivated to use the platform as well
SI2	If a celebrity, influencer, or blogger whom I admire shares a travel video on TikTok, I am inclined to engage with the platform
SI3	The suggestions of individuals in my social network will influence my inclination to use TikTok for selecting travel destinations
SI4	In general, the organization has supported the use of TikTok
Hedonic motivation (Zhou et al., 2023)	
HM1	The tourism-related short videos on TikTok are engaging and enjoyable
HM2	Viewing short travel videos on TikTok positively influences my emotional state
HM3	I am inclined to utilize TikTok as a tool for selecting travel destinations
Habit (Zhou et al., 2023) (Sia et al., 2023)	
HA1	I am used to using TikTok to watch short travel videos
HA1	I use TikTok when I need travel information
HA1	It is natural for me to use TikTok to help me make destination decisions when I need to
HA4	I'll be able to use TikTok without thinking
Facilitating conditions (Venkatesh et al., 2003)	
FC1	I possess the necessary resources, such as a mobile device and internet access, to use TikTok
FC2	I am proficient in using TikTok to search for short travel videos
FC3	When I encounter difficulties using TikTok, I can seek assistance from others or contact customer support
Behavioral intention (Zhou et al., 2023)	
BI1	I am interested in exploring and learning how to use TikTok for making destination decisions
BI2	I am inclined to continue using TikTok for making destination decisions in future travel
BI3	I would be inclined to suggest that others utilize TikTok for gathering information to make destination decisions
Use behavior (Zhou et al., 2023)	
UB1	I intend to use TikTok as a tool for making decisions regarding travel destinations
UB2	If I have been using TikTok, I will maintain its use for making destination decisions in the future
UB3	I intend to suggest to my friends and family that they use TikTok for making destination decisions

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Authors contributions

Zhikun Wang, Dr. Syafila and Dr. Hani were responsible for study design and revising. Zhikun Wang responsible for data collection, data analysis and drafted the manuscript. Dr. Syafila and Dr. Hani revised it. All authors read and approved the final manuscript. All authors contributed equally to the study.

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Competing interests

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

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Obtained.

Ethics approval

The Publication Ethics Committee of the Redfame Publishing.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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