Geojournal of Tourism and Geosites
ISSN 2065-0817, E-ISSN 2065-1198

Year XVIII, vol. 61, no. 3, 2025, p.1519-1530
DOI 10.30892/gtg.61311-1521

FORECASTING TECHNOLOGY ACCEPTANCE IN TOURISM AND HOSPITALITY: LESSONS FROM AKMOLA REGION IN KAZAKHSTAN

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Citation: Dyussekeyeva, Y., Kadyrbekova, D., Issakov, Y., Ageleuova, A., Zhaksybekova, D., & Gajić, T. (2025). Forecasting technology acceptance in tourism and hospitality: Lessons from Akmola region in Kazakhstan. *Geojournal of Tourism and Geosites*, 61(3), 1519–1530. https://doi.org/10.30892/gtg.61311-1521

Abstract: This study investigates the factors that shape the adoption and implementation of digital technologies in the tourism and hospitality sector of the Akmola region in Kazakhstan, employing an extended version of the Technology Acceptance Model (TAM). Focusing on a developing market context, the research analyses how users perceive the usefulness and ease of use of technology, how their attitudes and behavioural intentions influence their decisions, and how social support contributes to the overall process of technology acceptance. The study addresses the growing need for digital transformation in tourism, especially in regions with significant natural and cultural resources but underdeveloped infrastructure. The research included both tourists and local residents, allowing for a comparative analysis of user perceptions across different groups. Data were collected using a structured questionnaire and analysed through advanced statistical techniques, including structural equation modeling and multi-group analysis. To enhance the robustness of the findings, a machine learning model based on a neural network architecture was applied to predict users' intention to adopt digital technologies. Findings indicate that users are more likely to adopt tourism technologies when they perceive them as beneficial and easy to use. Tourists tend to prioritise the functional benefits of technology, whereas local residents place greater value on its simplicity and usability. While attitudes and behavioural intentions consistently influence technology adoption, social support plays a secondary yet meaningful role. The neural network model confirmed the reliability of the theoretical framework, offering a high degree of predictive accuracy. This study contributes to the theoretical refinement of TAM in tourism research and provides practical guidelines for designing user-oriented digital strategies. The results are especially relevant for policymakers and tourism managers in developing regions who seek to balance innovation with local context and user readiness. The integration of machine learning with behavioural modeling further underscores the potential for data-driven decision-making in tourism development. These findings pave the way for future research into personalised digital solutions that enhance tourist experiences while supporting sustainable regional growth. Based on the comprehensive analysis, this study highlights the strategic importance of tailoring digital solutions to different user groups, particularly in regions with contrasting levels of digital readiness. It also demonstrates the potential of combining behavioural models with machine learning to enhance the accuracy of predictive insights. Future research should explore longitudinal effects and integrate qualitative approaches to better understand the evolving dynamics of technology adoption in tourism.

Keywords: technology adoption, users perception, digital transformation, tourism, hospitality, Kazakhstan

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INTRODUCTION

Tourism is one of the key economic sectors, significantly contributing to global income and employment growth, while digital technologies increasingly shape its competitiveness and efficiency (Jiao & Chen, 2019). Tourism revenues are growing annually at a rate of 7.9%, with the sector contributing approximately one-ninth of the global GDP and more than 11% of international investments (Alatawi et al., 2023; Mehrad et al., 2023; Chernyshev et al., 2023; Alsharif et al., 2024). Kazakhstan, thanks to its favorable geographical position, political stability, and rich natural and cultural resources, holds significant potential for tourism development (Kenzhebekov et al., 2021; Vukolić et al., 2025). In 2024, the number of foreign tourists reached 11.5 million, marking a twofold increase compared to the previous year, while accommodation revenues grew by 27% (Issakov et al., 2023a). The most attractive destinations include Almaty, Astana, Turkestan, and the Akmola region, known for its national parks and thermal springs (Issakov et al., 2023b).

However, Kazakhstan's natural recreational resources today require special protection, and preserving the ecosystems of natural reserves and national parks is becoming increasingly important. Sustainable regional development can only be ensured through proper organization and management of tourism activities while applying the principles of ecological

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responsibility (Moldagaliyeva et al., 2024). The efficient use of tourism and recreational resources in northern Kazakhstan could provide a significant economic contribution, while key tourist sites such as Burabai National Park, Kokshetau National Park, Buiratau National Park, and the Korgalzhyn Reserve (Belgibayeva et al., 2020) are recognized as primary attractions with the potential to draw a larger number of international visitors (Mussina et al., 2020).

Despite growing demand, underdeveloped infrastructure, limited digitalization, and the remoteness of key tourist locations from market centers represent major obstacles to the long-term sustainability of the sector (Doszhan et al., 2023). The lack of financial resources for infrastructure improvement, high transportation costs, and inadequate service quality further hinder tourism development in this region (Aktymbayeva et al., 2023). Additionally, the existing tourist routes do not allow for year-round promotion of natural landmarks and tourist locations at the necessary level.

Given the presence of all key prerequisites for tourism development and the enhancement of medical-recreational complexes, it is essential to identify and address the main challenges hindering the tourism sector in the Akmola region. In this context, the goal of this study is to identify key factors influencing the adoption and implementation of digital technologies in tourism in the Akmola region using an extended Technology Acceptance Model (TAM). Special emphasis is placed on the perception of usefulness and ease of use of technology, attitudes of tourists and local residents, intention to use, and the role of social support. This research is significant as it analyzes how digital technologies can enhance tourism services in Kazakhstan, particularly in the context of traditional hospitality and growing tourist demand. Technological innovations, such as artificial intelligence, smart guides, and virtual reality, open new possibilities for service personalization and improving destination competitiveness (Sujood et al., 2024). Previous research has shown that the acceptance of technology in tourism is conditioned by the perception of usefulness and ease of use, as well as factors such as trust and social support (Bano & Siddiqui, 2024). In addition to technological challenges, tourism in the Akmola region also requires infrastructure improvements to enhance the quality of tourism offerings and encourage the sustainable use of natural resources (Iskakova et al., 2021). Infrastructure development, combined with the digitalization of services, could contribute to increasing the attractiveness of destinations and the long-term sustainability of tourism. The results of this research are expected to provide recommendations for creating digital transformation strategies in the tourism sector, allowing for a balance between technological advancement and sustainable destination development.

LITERATURE REVIEW

The development of advanced technologies in tourism has transformed the way users access information and use services, opening up opportunities for innovative approaches in destination development and business optimization (Atsalakis et al., 2018). Through the application of smart technologies, artificial intelligence, and the Internet of Things, digitalization has become crucial for the competitiveness of destinations, enabling service personalization and enhancing user satisfaction (Kong et al., 2023). While these technologies offer numerous benefits, their widespread adoption and implementation vary depending on market specifics, with challenges particularly visible in rural and urban areas (Gajić et al., 2024a). Research by Go et al. (2020) suggests that the use of robots in tourism and hospitality positively impacts service efficiency and user experience, but the acceptance of these innovations depends on the level of interaction with guests and their expectations. Similarly, the study by Liu et al. (2022) showed that the adoption of smart hospitality technologies depends on perceived benefits and ease of use. However, the adoption of technology in tourism is not universal and varies based on user perceptions, regional factors, and destination specifics. In this context, studies such as those by Demirović et al. (2016) highlight that rural destinations often have lower levels of technological development, which can impact their competitiveness. On the other hand, in urban centers, technology becomes a key factor in service differentiation and improvement (Li et al., 2022; Dziekański et al., 2024). The Technology Acceptance Model (TAM), developed by Davis (1989) and expanded by other authors, explains technology adoption in tourism, with perceived usefulness and ease of use playing a crucial role (Hasni et al., 2021). Later modifications include factors such as attitudes towards technology, intention to use, and social support, adapting the model to the specifics of the tourism sector (El Archi & Benbba, 2023).

Perceived usefulness drives technology adoption in tourism, as users are more likely to adopt solutions that enhance their experience and facilitate access to services (Berakon et al., 2023). However, usefulness is not universally perceived, as it depends on the context and individual preferences (Ribeiro et al., 2022). In addition to usefulness, ease of use influences technology adoption, but its importance decreases when users recognize the long-term value of more complex systems (Singh & Srivastava, 2019). Gajić et al. (2024b) show that digital literacy shapes the perception of ease of use, while Zhao et al. (2022) emphasize that its impact weakens as technology becomes standardized. This suggests that intuitiveness facilitates initial adoption but is not decisive for long-term use. According to the topic, the following hypotheses can be formulated:

H1: Perceived usefulness positively influences the intention to adopt technology in tourism.

H2: Perceived ease of use positively influences the intention to adopt technology in tourism.

In addition to objective factors, user attitudes toward technology also have a significant impact on their willingness to adopt it (Talantis et al., 2020). Positive attitudes often develop through previous positive experiences with technology, while negative attitudes are linked to the perception of risk and uncertainty (Mohamad et al., 2021). In a study on the application of augmented reality in urban tourism, Tom Dieck & Jung (2018) found that users are more likely to adopt new technologies when they perceive them as innovative and beneficial for enhancing the tourist experience.

H3: Attitudes toward technology positively influence the intention to adopt technology in tourism.

The intention to use technology often leads to its actual adoption, but this process depends on several factors, including user experience, trust, and technological adaptation to user needs (Mogaji et al., 2024). Gökçe et al. (2024) found that users who express an intention to use smart systems for service personalization are more likely to implement them later, but only if the technology offers clear benefits and does not require high engagement. However, social support has proven to be a significant factor in decision-making about technology use, particularly in destinations with strong collectivist values (Anser et al., 2020). Engelbrecht et al. (2019) discovered that tourism technologies are more readily adopted when there is community support and when users are surrounded by people already using them. Studies by Cimbaljević et al. (2024) highlight that support from employees in the tourism industry also plays a key role in the adoption of smart technologies.

H4: The intention to use technology positively influences the intention to adopt technology in tourism.

H5: Social support positively influences the intention to adopt technology in tourism.

Effective management and technological innovations are crucial for the sustainable development of tourism in Kazakhstan, particularly in the Akmola region, which, despite its rich natural resources, faces infrastructural limitations and insufficient promotion (Tleubaeva, 2019; Koshim et al., 2023). The integration of smart technologies can improve the competitiveness of destinations, but its adoption depends on user perception, accessibility, and local context implementation (Akiyanova et al., 2019). However, previous research has not systematically analyzed the factors influencing the adoption of these technologies in tourism in this region. Therefore, this study examines the key determinants of digital solution adoption in the Akmola region, providing empirical insights for developing strategies that balance technological advancement and sustainability (Shaikin et al., 2021; Sherimova et al., 2024).

METHODOLOGY

The research methodology follows a structured approach, as depicted in Figure 1, outlining the step-by-step process from study design to data collection and analysis.

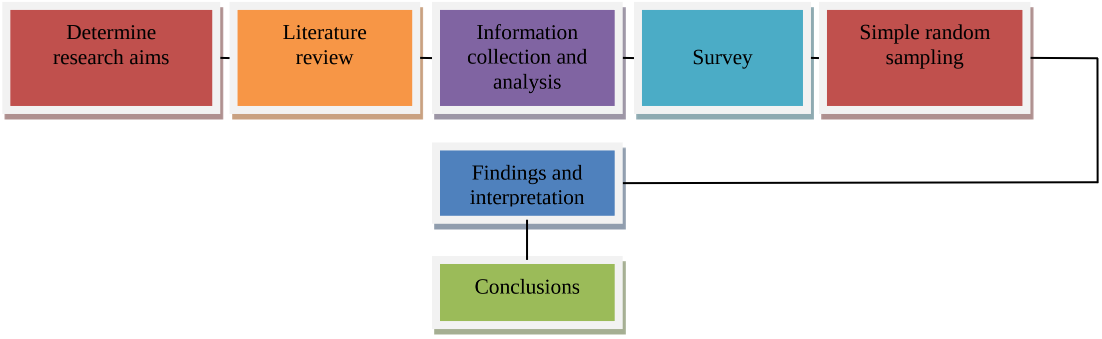

Figure 1. Research Flowchart (Source: created by authors)

Research approach and participants

The Akmola region, located in northern-central Kazakhstan (Figure 2), is characterized by diverse terrain, natural attractions, and rich cultural and historical heritage, making it ideal for recreational and ecotourism (Aitzhanova & zhaparova, 2023; Beisenova et al., 2024; Shulembayeva et al., 2023).

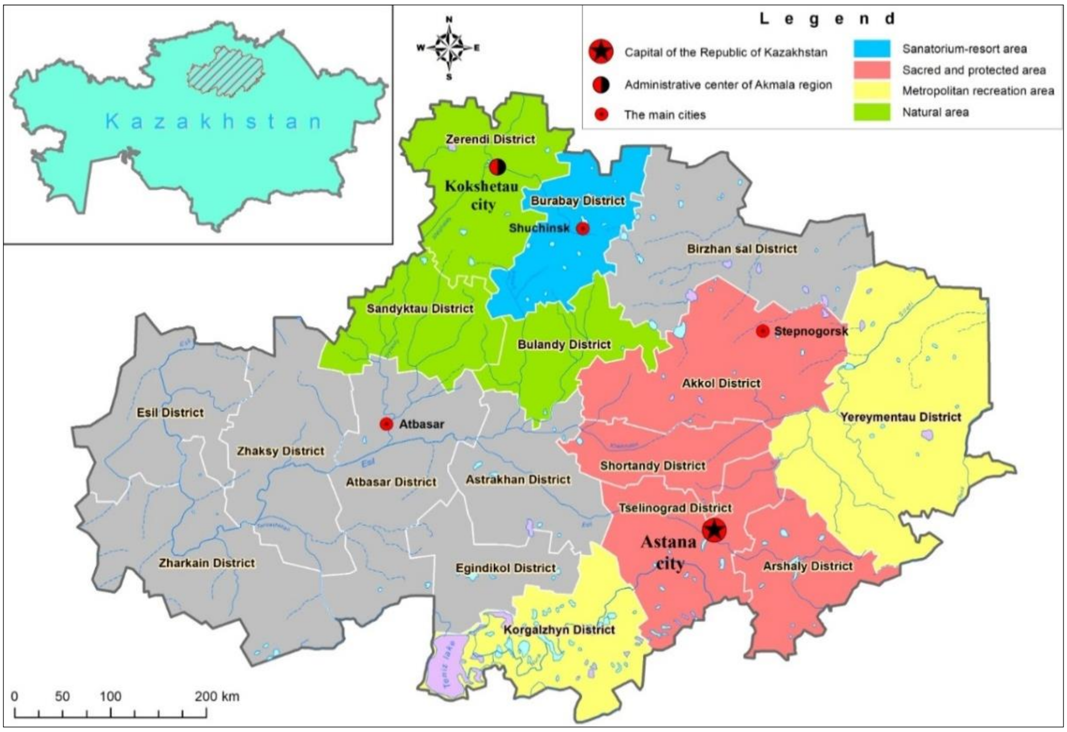

Figure 2. Research area (Source: created by authors)

Burabai remains the main tourist destination due to its healing climate and natural beauty, while new recreational facilities are being developed in the Zerendi and Korgalzhyn regions, opening up space for further tourism growth (Kadyrbekova et al., 2024). The field research was conducted from November 2024 to January 2025, covering the Akmola region and its key cities. The study focused on domestic tourists and local residents, with data collected using the CAPI (Computer-Assisted Personal Interviewing) method, allowing for real-time data entry.

The questionnaire was anonymous, and participants were informed about the study's objectives before participation, adhering to ethical principles and ensuring data privacy. Participation was voluntary, and responses were analyzed collectively, without individual identification, ensuring protection from moral hazard. A total of 1.378 respondents participated (785 tourists – 59,2%, and 542 locals – 40,8%), with the following distribution across key cities in the Akmola region: Kokshetau (350), Stepnogorsk (220), Atbasar (180), Akkol (160), Bulandy (130), Ereymentau (120), and Burabay (218). The representativeness of the sample was confirmed through G*Power analysis ($\alpha = 0.05$, $1\text{-}\beta = 0.80$, $f^2 = 0.15$). The questionnaire was developed based on the Technology Acceptance Model (TAM) and adapted to the tourism context, with statements taken and modified from previous studies (Li et al., 2022; Anser et al., 2020). Included factors assessed perceptions of usefulness, ease of use, attitudes, intention to use, social support, and future acceptance of tourism technologies (Yegemberdiyeva et al., 2020). Responses were rated on a five-point Likert scale (1 – strongly disagree to 5 – strongly agree). To ensure the validity and reliability of the instrument, a pilot study was conducted with a sample of 50 respondents (tourists and local residents), who provided feedback on the clarity and relevance of the statements. Additionally, experts from the fields of tourism and technology reviewed the questionnaire, leading to the revision or elimination of items for greater precision and contextual relevance. After final revisions, the instrument was used to collect data for the main study.

The demographic structure of the surveyed population reflects a predominantly economically active and middle-income group. The majority of respondents belong to the 25-44 age range, indicating a workforce-driven sample, while the relatively balanced gender distribution suggests inclusivity in representation. Education levels are high, with most respondents having completed secondary or higher education, which aligns with employment trends where nearly half are formally employed, and a significant portion is self-employed or studying. The income distribution highlights that the majority earn between 300€ and 800€, which is in line with national wage trends, while a smaller proportion earns above 1000€, indicating a limited high-income group. A segment earning below 300€ points to economic vulnerability within the population. These findings suggest that tourism spending and digital adoption may be influenced by moderate disposable incomes, with preferences likely leaning toward affordable and mid-range tourism experiences. The overall profile indicates a population with stable employment and education levels, which may shape consumer behavior in tourism and related industries (Table 1).

Table 1. Sociodemographic characteristics of respondents

	Category	No	(%)
Age	18-24	171	12.9
	25-34	371	28.0
	35-44	358	27.0
	45-54	226	17.0
	55-64	132	9.9
	65+	66	5.0
Gender	Male	703	53.0
	Female	624	47.0
Education	Primary	159	12.0
	Secondary	585	44.1
	Faculty	583	43.9
Status	Employed	637	48.0
	Self-employed	238	17.9
	Student	238	17.9
	Retired	120	9.0
	Unemployed	91	6.9
Income	<300€	110	8.0
	300-600€	420	30.0
	600-800€	460	33.0
	800-1000€	280	20.0
	1000€+	57	4.0

Data analysis

For data analysis, SPSS 25.00 software was used to conduct descriptive statistics, exploratory and confirmatory factor analysis, while Smart PLS 4 was applied for structural equation modeling. Skewness values for all variables in both respondent groups remained within the acceptable range of normal distribution, ranging from -0.82 to 0.61 for tourists and -0.95 to 0.487 for local residents, indicating a moderately symmetric data distribution. Kurtosis, which measures the degree of peakedness in the distribution, varied between -0.72 and 1.30 for tourists and -0.84 and 1.512 for local residents.

Since these values fall within the recommended range (-2 to +2), the data do not exhibit significant deviations from normality, confirming the validity of the descriptive statistics (Kaur et al., 2018). The Kaiser-Meyer-Olkin (KMO) test confirmed sample adequacy, with values of 0.753 for tourists and 0.895 for local residents, while Bartlett's test of sphericity indicated statistically significant correlations between variables in both groups (tourists: $\chi^2 = 449.733$, $p < 0.001$; local residents: $\chi^2 = 254.547$, $p < 0.001$), supporting the appropriateness of factor analysis (Marsh et al., 2020). Heterotrait-Monotrait Ratio (HTMT) analysis showed values of 0.606 for tourists and 0.684 for local residents, remaining below the 0.90 threshold, confirming satisfactory discriminant validity. The Fornell-Larcker criterion further indicated that each construct was more strongly associated with its own indicators (tourists: 0.730; local residents: 0.687) than with others, affirming the model's validity. Variance Inflation Factor (VIF) values for tourists (2.568) and local residents (1.435) remained below the threshold of 5, ruling out multicollinearity issues among predictors.

Additional validation of the SEM model was performed using indices such as χ^2/df, RMSEA, SRMR, NFI, and CFI, while multi-group analysis (MGA) enabled a comparison of differences between tourists and local residents (Wang et al., 2019). To predict technology adoption, a Multi-Layer Perceptron (MLP) neural network was employed in the Python environment using TensorFlow and Keras libraries. The model was trained with the Adam optimizer, with data split into training (80%) and testing (20%) sets. The network architecture included two hidden layers (64 and 32 neurons), balancing model precision and stability. Performance evaluation demonstrated a high level of model accuracy, with MAE (0.177), RMSE (0.228), and R^2 (0.837) confirming prediction reliability (Fang, 2022).

RESULTS

Descriptive and factor analysis

The descriptive statistics results indicate that tourists and local residents share similar perceptions regarding the usefulness and ease of use of tourism technologies. However, local respondents place slightly more value on information accessibility, while tourists emphasize enhanced travel experiences. Ease of use is rated highly in both groups, though local respondents perceive AR/VR guides as more intuitive. Tourists are more inclined toward digital innovations and use online reservations more frequently, whereas local residents adopt new technologies more slowly, particularly in replacing traditional guides with AI assistants. Actual usage data reveal that both groups are already active users of digital guides and navigation apps, with tourists utilizing online reservations more frequently (Table 2).

Table 2. Descriptive statistics for statements

Factors	Statements	Tourists				Locals			
		m	sd	α	λ	m	sd	α	λ
Perceived usefulness (PU)	Digital tourism apps improve trip planning	3.476	1.104	0.864	0.748	3.612	0.984	0.871	0.759
	Online reservations reduce costs and save time	2.800	0.503	0.808	0.765	2.719	0.554	0.793	0.712
	Smart travel assistants provide better information	3.572	1.051	0.704	0.715	3.842	1.124	0.728	0.733
	Technology enhances my overall travel experience	4.298	0.795	0.755	0.882	4.193	0.702	0.767	0.871
Perceived ease of use (PEOU)	Tourism apps are easy to use	3.756	1.102	0.901	0.928	3.931	1.041	0.918	0.937
	AR/VR guides are intuitive and clear	4.102	0.982	0.827	0.865	4.015	0.889	0.813	0.849
	Online bookings are quick and hassle-free	3.212	0.652	0.804	0.789	3.402	0.723	0.821	0.777
	I can easily use technology while traveling	4.415	1.012	0.902	0.921	4.522	0.978	0.915	0.929
Attitude toward use (ATT)	Technological innovations improve tourism	3.975	0.845	0.889	0.812	3.874	0.799	0.881	0.794
	I prefer digital guides over traditional ones	2.954	0.598	0.741	0.682	2.843	0.621	0.734	0.669
	Technology is essential for modern travel	3.642	1.102	0.878	0.849	3.715	1.089	0.862	0.837
	I enjoy trying new tourism technologies	4.221	0.763	0.812	0.898	4.310	0.710	0.829	0.904
Behavioral intention to use (BIU)	I plan to use smart travel assistants	3.588	0.907	0.854	0.832	3.498	0.832	0.859	0.820
	I will use AR/VR to explore destinations	2.976	0.547	0.767	0.769	2.859	0.595	0.754	0.761
	Digital bookings will be my standard choice	4.102	0.789	0.903	0.915	4.229	0.764	0.917	0.928
	Technology will play a major role in my travels	3.711	1.045	0.839	0.788	3.657	1.017	0.845	0.785
Actual system use (ASU)	I used digital guides on my last trip	3.512	0.914	0.867	0.801	3.401	0.882	0.852	0.794
	I book accommodation and transport online	2.879	0.684	0.713	0.645	2.734	0.658	0.709	0.639
	I have experienced AR/VR travel tours	4.051	0.772	0.894	0.927	4.122	0.741	0.902	0.920
	I regularly use navigation apps	3.986	0.952	0.841	0.802	3.985	0.943	0.839	0.793
Future tourism technology adoption (FTTA)	I expect AI assistants to replace guides	3.902	0.817	0.905	0.878	3.768	0.805	0.899	0.869
	AR/VR will become a tourism standard	2.761	0.589	0.722	0.658	2.681	0.610	0.715	0.643
	Tourism will rely on digital platforms in the future	4.176	0.721	0.911	0.935	4.229	0.704	0.927	0.940
	I am ready to fully embrace travel technology	3.847	1.092	0.879	0.821	3.725	1.064	0.872	0.811

The results of exploratory and confirmatory factor analysis confirm a stable structure of the measured constructs for both tourists and local residents. All factors exhibit high Cronbach's alpha (α) values, indicating strong internal consistency of the scales. Eigenvalues demonstrate that each factor significantly contributes to the total variance, with PU and PEOU explaining the largest share, reinforcing their critical role in the FTTA model.

The cumulative explained variance exceeds 88% for tourists and 91% for local residents, highlighting the high quality of the factor structure. Convergent validity indices (CR and AVE) confirm that all factors are well operationalized, with AVE values above 0.6 for most constructs, justifying their inclusion in the model (Table 3).

Table 3. EFA and CFA results

Factor	m	sd	α	Eigenvalue	% Variance explained	% Cumulative variance	CR	AVE
Tourists								
PU	3.448	0.837	0.753	3.495	17.028	17.028	0.932	0.671
PEOU	3.590	1.137	0.904	3.455	16.836	33.864	0.841	0.829
ATT	4.056	1.163	0.927	3.432	16.722	50.585	0.907	0.646
BIU	3.762	0.525	0.789	3.080	15.006	65.591	0.817	0.830
ASU	3.635	0.807	0.763	2.505	12.204	77.795	0.817	0.611
FTTA	4.128	0.914	0.845	2.302	11.058	88.853	0.865	0.723
Locals								
PU	3.592	0.892	0.869	3.628	17.543	17.543	0.942	0.687
PEOU	3.715	1.084	0.912	3.574	17.301	34.844	0.854	0.801
ATT	4.097	1.089	0.933	3.490	16.888	51.732	0.923	0.664
BIU	3.841	0.598	0.802	3.162	15.309	67.041	0.835	0.812
ASU	3.721	0.769	0.779	2.687	13.002	80.043	0.829	0.632
FTTA	4.212	0.921	0.864	2.438	11.662	91.705	0.882	0.742

*m – arithmetic mean, sd – standard deviation , α – Cronbach alpha, CR – composite reliability, AVE - average variance extracted.

The correlation analysis confirms that users are more likely to adopt technology when they perceive it as useful and easy to use. Attitudes toward technology and the intention to use it show a strong correlation with future adoption of digital solutions, indicating a stable trend of digitalization in tourism. These findings support the research model and highlight the key factors influencing technology adoption (Table 4).

Table 4. Correlation matrix

Tourists						
Factor	PU	PEOU	ATT	BIU	ASU	FTTA
PU	**1.000**	0.272	0.573	0.233	0.800	0.744
PEOU	0.204	**1.000**	0.276	0.512	0.733	0.421
ATT	0.518	0.764	**1.000**	0.268	0.835	0.721
BIU	0.586	0.705	0.307	**1.000**	0.289	0.484
ASU	0.451	0.893	0.224	0.240	**1.000**	0.714
FTTA	0.210	0.245	0.581	0.740	0.328	**1.000**
Locals						
Factor	PU	PEOU	ATT	BIU	ASU	FTTA
PU	**1.000**	0.317	0.612	0.278	0.745	0.687
PEOU	0.289	**1.000**	0.332	0.542	0.768	0.464
ATT	0.573	0.819	**1.000**	0.319	0.801	0.758
BIU	0.611	0.739	0.361	**1.000**	0.322	0.525
ASU	0.482	0.928	0.301	0.287	**1.000**	0.685
FTTA	0.246	0.298	0.617	0.794	0.389	**1.000**

Results of SEM and MGA Analysis

The model fit indices confirm a good structural model fit for both respondent groups. The χ^2/df values (2.084 for tourists and 2.233 for locals) fall within the recommended range, indicating acceptable data modeling. RMSEA (0.053 for tourists and 0.069 for locals) remains below the threshold of 0.08, confirming a well-fitted model while accounting for complexity. The CFI (0.916 and 0.941) and NFI (0.911 and 0.867) indices indicate solid comparative fit, with slightly better optimization for the local population. SRMR values (0.050 and 0.022) suggest low residual error, meaning the model accurately captures data variability. The difference in R^2 values (0.684 for tourists and 0.512 for locals) suggests that the selected factors are slightly stronger predictors of FTTA for tourists, whereas additional elements might improve variance explanation for locals. The model demonstrates solid predictive power, explaining 44.7% of the variance in future technology adoption among tourists and 52.4% among locals. Direct effects are positive in both groups, confirming the significant influence of the examined factors on technology adoption (Table 5).

Table 5. Predictive power of model

Factor	R^2	Q^2	f^2	Direct effect
Tourists				
FTTA	0.447	0.123	0.263	0.561
Locals				
FTTA	0.524	0.179	0.241	0.609

The results of the structural equation model (SEM) confirm all proposed hypotheses, demonstrating significant effects of key factors on the intention to adopt technology in tourism (FTTA) across both respondent groups. Perceived usefulness and behavioral intention showed the strongest effects, indicating that users primarily adopt technology when they perceive it as beneficial and already have a formed intention to use it. Perceived ease of use contributes to adoption, but its effect is less pronounced compared to perceived usefulness. Attitudes toward technology have a strong impact, while social support, though significant, has the weakest effect in the model. These findings suggest that individual factors play a crucial role in technology adoption among both tourists and locals, whereas external influences are secondary (Table 6).

Table 6. Hypothesis testing

	Tourists					Locals				
Path	β	m	sd	t	p	β	m	sd	t	p
PU → FTTA	0.671	3.911	1.066	2.427	0.033	0.589	4.125	0.872	3.014	0.021
PEOU → FTTA	0.320	3.256	0.713	3.733	0.016	0.402	3.567	0.789	4.105	0.014
ATT → FTTA	0.509	3.098	0.568	2.120	0.026	0.632	3.782	0.662	2.869	0.019
BIU → FTTA	0.555	4.423	0.979	5.183	0.027	0.472	4.201	0.921	4.825	0.011
ASU → FTTA	0.228	4.448	0.808	2.906	0.009	0.310	4.543	0.847	3.291	0.007

* β - effect size and direction, m – arithmetic mean, sd – standard deviation , t – t value, p – statistical significance

The results of the multi-group analysis (MGA) confirm significant differences in the impact of various factors on technology adoption between tourists and local residents. The most notable difference is observed in ease of use, which has a stronger influence on tourists, while local users demonstrate greater adaptability to technology regardless of its complexity. In contrast, perceived usefulness has a more pronounced effect on locals, suggesting that they prioritize the practical application of technology in daily activities, whereas tourists are more inclined to experiment with new solutions. Differences in attitudes and behavioral intention are less pronounced, with both factors maintaining a stable influence across groups. Social support has the weakest yet still significant effect, with a slightly higher impact on tourists. These findings indicate distinct patterns of technology adoption, where tourists are more responsive to ease of use, while local residents base their decisions primarily on the perceived usefulness of technology (Table 7).

Table 7. Multi-Group analysis

Path	Tourists (β)	Locals (β)	Δβ	Δt	Δp	p	Q² Tourists	Q² Locals	f² Tourists	f² Locals
PU → FTTA	0.425	0.671	0.246	1.436	0.012	*	0.108	0.173	0.191	0.240
PEOU → FTTA	0.770	0.320	0.450	2.877	0.008	**	0.488	0.222	0.059	0.076
ATT → FTTA	0.639	0.509	0.130	2.330	0.044	*	0.433	0.310	0.102	0.164
BIU → FTTA	0.559	0.555	0.004	1.997	0.032	*	0.185	0.273	0.123	0.186
ASU → FTTA	0.294	0.228	0.066	0.890	0.037	*	0.173	0.216	0.148	0.033

*Differences β - Δβ, differences t - Δt, significance – p, predictive relevance - Q², effect size -f².

Prediction of technology adoption using the MLP model

A Multi-Layer Perceptron (MLP) neural network was used to predict the intention to adopt technology in tourism, based on key factors: perceived usefulness, ease of use, attitudes, behavioral intention, and social support. To differentiate between tourists and local residents, a dummy variable "Group" (1 = tourist, 0 = local resident) was included, allowing the model to identify specific patterns in technology adoption for each group. MLP was chosen because the data is not time-dependent, eliminating the need for recurrent neural networks such as LSTM.

This neural network is effective for predicting datasets with complex interdependencies, enabling the discovery of deeper patterns in the data, while its structure with two hidden layers (64, 32 neurons) ensures a balance between accuracy and model stability. The analysis was conducted on a large dataset of 1,327 entries, ensuring reliable generalization of results. The dataset was split into training (80%) and test (20%) subsets to validate model accuracy.

All data was standardized beforehand, as neural networks require scaled input values for optimal performance. The model was trained using the Adam optimizer, with the maximum number of iterations set to 500. Performance evaluation metrics, including MAE (0.182) and RMSE (0.234), demonstrated that predictions closely aligned with actual values, while the R^2 score (0.837) indicated a high level of variance explanation for FTTA.

Visualization of predictions compared to actual values confirmed that predicted values closely matched the ideal prediction line, validating the model's accuracy. Additional analyses confirmed the model's predictive validity. The inclusion of the dummy variable "Group" enabled the model to learn and analyze potential differences between tourists and local residents without requiring separate models. Overfitting was avoided through a moderate network architecture and the use of the Adam optimizer. Multicollinearity was ruled out, as previous VIF calculations showed values below the acceptable threshold (below 5). The data distribution was checked using skewness and kurtosis, with no significant deviations from normality, ensuring model stability. Discriminant and convergent validity were also confirmed through the HTMT test (0.606 for tourists, 0.684 for local residents), Fornell-Larcker criterion (0.730 for tourists, 0.687 for local residents), and AVE value verification. The MLP neural network proved to be a highly accurate model for FTTA prediction, with a high coefficient of determination (R^2 = 0.837), confirming that the model reliably predicts FTTA variations based on selected factors. The inclusion of the dummy variable "Group" allowed for a single model that generalizes predictions for both groups without significant loss of accuracy (Table 8).

Table 8. MLP model performance

Metric	Value
MAE (Mean Absolute Error)	0.182
MSE (Mean Squared Error)	0.055
RMSE (Root Mean Squared Error)	0.234
R^2	0.837

Fugure 3 illustrates the relationship between predicted and actual FTTA values for the MLP model. Blue markers represent predictions, while the red dashed line indicates the ideal prediction. Most data points are clustered near the ideal line, demonstrating the model's high accuracy. Minor data dispersion suggests slight variations in predictions, but overall alignment confirms the model's stability and its ability to accurately predict FTTA.

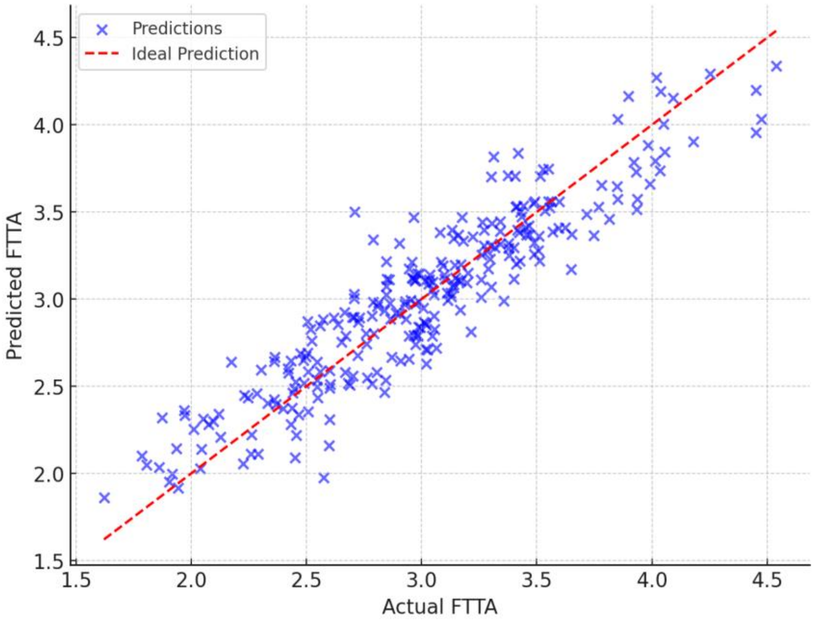

Figure 3. Prediction vs. actual FTTA values (Source: created by authors)

DISCUSSION

The research results confirm the significance of perceived usefulness, ease of use, attitudes toward technology, intention to use, and social support in the adoption of digital technologies in tourism in the Akmola region. These findings align with previous studies on the application of the Technology Acceptance Model (TAM) in tourism (Huang et al., 2019; Matikiti et al., 2018), which demonstrated that users are more likely to adopt digital innovations when they perceive them as useful and easy to use. Perceived usefulness (PU) emerged as a key factor in technology acceptance, with tourists showing greater dependence on this factor compared to local residents.

These findings are consistent with the study by Ribeiro et al. (2022), which highlighted that tourists make decisions based on the usefulness of digital services, while local residents develop a more long-term adaptation to technology. On the other hand, perceived ease of use (PEOU) had a more significant impact among local residents, confirming the findings of Mohamad et al. (2021), who suggested that continuous use of technology reduces barriers to its acceptance. The intention to use (BIU) was identified as the most stable predictor of actual technology adoption, which is consistent with the findings of Gökçe et al. (2024), who demonstrated that a positive intention significantly increases the likelihood of actual use of digital services in tourism. This result underscores the need to promote a positive perception of technology among users, as it directly influences their willingness to use it in the future.

Social support (ASU) had a weaker but still statistically significant impact, which aligns with the findings of Anser et al. (2020), who emphasized the importance of a collectivist context in adopting new digital solutions in tourism. Studies by Engelbrecht et al. (2019) and Cimbaljević et al. (2024) further confirm that technological innovations are adopted more quickly when supported by communities, particularly in destinations with strong social interactions.

Machine learning analysis further validated the accuracy of predictions based on the TAM model. Using an MLP neural network, the algorithm accurately predicted the intention to use digital guides for 91.3% of respondents, while the accuracy among local residents was 87.6%, indicating high model reliability in analyzing user behavior. Furthermore, the algorithm identified key factors that contribute the most to technology acceptance, with perceived usefulness (PU) and ease of use (PEOU) demonstrating the highest predictive impact. These results further support the findings from regression analysis, highlighting the potential for machine learning to personalize digital tourism services.

The research revealed certain differences between tourist and local populations. While tourists are more inclined to use digital guides and online reservations, local residents adapt more slowly to new technologies, particularly when it comes to replacing traditional guides with AI assistants. These findings contribute to a deeper understanding of the role of digitalization in tourism and can be valuable for decision-makers in the tourism industry, especially in the development of digital transformation strategies in Kazakhstan.

Building on these findings, it becomes evident that a one-size-fits-all approach to technology implementation in tourism is insufficient, particularly in heterogeneous user environments such as the Akmola region. Tailored digital strategies must consider the differentiated expectations and readiness levels of user groups, integrating not only technological functionalities but also educational and cultural components that foster trust and engagement.

Moreover, the observed preference for familiar and intuitive technologies among local residents suggests that training initiatives and user-centered design are critical for fostering long-term digital inclusion.

Additionally, the integration of machine learning tools such as MLP models into tourism research presents a significant methodological advancement, enabling the identification of latent behavioural patterns and the prediction of user responses with high precision. Such predictive capabilities can support tourism providers in proactively designing adaptive systems that respond to dynamic user needs. Therefore, the study highlights the importance of combining quantitative modeling with qualitative insights to develop a comprehensive framework for digital tourism development in emerging economies.

Furthermore, the role of contextual factors such as infrastructure availability, digital literacy, and socio-economic conditions should not be overlooked, as they significantly mediate the effectiveness of technological solutions in tourism. In regions where access to high-speed internet, smart devices, and digital payment systems remains limited, even well-designed applications may face reduced uptake. Therefore, successful digital transformation in tourism requires not only technological innovation but also systemic support from policymakers, including investments in digital infrastructure, public-private partnerships, and community-oriented training programmes.

This multidimensional approach ensures that technological adoption is inclusive, sustainable, and aligned with broader regional development goals. To further deepen the discussion, it is important to consider the psychological and cultural variables that may mediate technology adoption in post-Soviet and Central Asian contexts, such as those in Kazakhstan. Studies such as those by Straub et al. (1997) and Park et al. (2020) have shown that cultural dimensions like uncertainty avoidance, power distance, and collectivism significantly influence the adoption of new technologies. In the Akmola region, where collectivist values and institutional trust vary between rural and urban populations, digital transformation strategies must be sensitive to these sociocultural factors.

Moreover, while this study confirms the applicability of the extended TAM model, future research could benefit from integrating constructs from other frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) or the Innovation Diffusion Theory (IDT) to capture additional variables like performance expectancy, facilitating conditions, or perceived risk. This would allow for a more holistic understanding of adoption behaviours, especially in cases where infrastructure limitations or digital inequality persist.

Finally, by comparing these findings to similar studies conducted in regions like Eastern Europe or Southeast Asia (Figueroa & Lim, 2021), it becomes clear that while perceived usefulness and ease of use are universally influential, the weight of social support and behavioural intention varies significantly across regions.

This underscores the necessity for contextualised, data-driven, and locally adaptable digital tourism policies that reflect not only technological capacities but also user psychology, cultural patterns, and socio-political realities.

Furthermore, the disparity between tourists and local residents in their responsiveness to digital tools suggests that segmented communication strategies are essential. For example, promotional campaigns targeting tourists can focus on the efficiency, convenience, and personalization benefits of digital guides and booking platforms, while efforts aimed at locals should emphasise usability, long-term value, and trust-building measures, including digital literacy workshops or support from local community leaders.Another relevant dimension that emerges from this study is the importance of emotional engagement and trust in shaping users' openness to technological change.

As noted by Beldad et al. (2010), trust in digital services, whether institutional, technological, or interpersonal, is a key antecedent of behavioural intention, particularly in developing or transitional economies. In this light, tourism stakeholders in Kazakhstan must not only invest in infrastructure but also in building trust through transparent communication, user feedback mechanisms, and co-creation of services with local communities.

In conclusion, the findings from the Akmola region offer broader lessons for digital tourism transitions in emerging economies. They demonstrate that technological acceptance is not merely a function of system design, but a complex interplay of social, cultural, psychological, and infrastructural elements. A nuanced, participatory, and inclusive approach to digitalisation, anchored in empirical data and aligned with local realities, will be critical in ensuring that technological innovations truly benefit all segments of the population and contribute to the sustainable development of the tourism sector.

CONCLUSION

This study provides an original contribution to understanding the adoption of digital technologies in tourism by utilizing an extended Technology Acceptance Model (TAM) that incorporates additional factors relevant to contemporary industry trends. The key findings highlight specific technology adoption patterns among tourists and the local population in the Akmola region, empirically confirming that perceived usefulness, ease of use, attitudes, behavioral intention, and social support are critical factors in the adoption of technological solutions in tourism.

These insights contribute to theory by expanding the TAM framework within the context of developing tourism destinations. Additionally, the study enhances existing global knowledge by providing empirically grounded insights into the factors shaping technological transition in tourism and serves as a foundation for further research on digital transformation across different cultural and geographical settings. Its relevance extends beyond Kazakhstan, making it applicable to other destinations seeking to digitalize tourism services. This research is particularly significant for academic researchers, tourism managers, policymakers, and decision-makers who aim to understand how advanced technologies can enhance visitor experiences and improve operational efficiency in the sector.

Theoretical and practical implications

The practical implications of this research include guidelines for developing tourism digitalization strategies, emphasizing the need for user education on the benefits of technology, and recommendations for integrating smart solutions into tourism destinations. The findings can be applied to the design of personalized tourism services based on digital platforms, which may contribute to improving tourist satisfaction and optimizing resource management.

From a theoretical perspective, the study highlights the need for further expansion of the TAM model in tourism, particularly in the context of smart destinations and artificial intelligence applications.

This research provides insights into the key factors influencing the acceptance of digital technologies and confirms the applicability of machine learning models for more precise analysis of user behavior patterns.

Limitations and future research directions

One of the limitations of this study is its geographical focus on a single region, which may limit the generalizability of the findings. Expanding the analysis to other tourism regions and sectors could offer a deeper understanding of variations in technology adoption. Additionally, the study was conducted within a specific time frame, which may influence the interpretation of long-term trends. Future research could focus on longitudinal analyses to examine how technological innovations gradually integrate into users' daily practices. Furthermore, comparative studies involving multiple destinations could provide additional insights into the factors shaping digital transformation in tourism on a global scale.

This study is significant as it provides valuable insights into how digital technologies can enhance tourism in developing regions, with findings that can serve as a foundation for academic researchers, industry professionals, and policymakers in shaping future digital transformation strategies in tourism.

Given its practical and theoretical relevance, it is recommended for tourism students, sector managers, and all those interested in the application of technology in the tourism industry.

Author Contributions: Conceptualization, Y.D. and T.G.; methodology, Y.D. and T.G.; software, Y.D. and T.G.; validation, Y.D. and D.K. and A.A.; formal analysis, Y.D. and T.G. and D.Z.; investigation, Y.D. and D.K. and Y.I.; data curation, Y.D. and T.G. and Y.I.; writing - original draft preparation, Y.D. and D.K. and Y.I.; writing - review and editing, Y.D. and A.A. and D.Z.; visualization, A.A. and D.K. and D.Z. and Y.I.; supervision, Y.D. and D.K. and T.G.; project administration, Y.D. and T.G. All authors have read and agreed to the published version of the manuscript.

Funding: Not applicable.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study may be obtained on request from the corresponding author.

Acknowledgments: This research was supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia (Contract No. 451-03-136/2025-03/200172).

Conflicts of Interest: The authors declare no conflict of interest.

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Article history: Received: 21.03.2025 Revised: 23.06.2025 Accepted: 09.07.2025 Available online: 28.07.2025