A Hybrid SEM-ANN Method for Developing an Information Technology Acceptance and Utilization Model in River Tourism Services

Mutia Maulida[1]*, Iphan Fitrian Radam[2], Nurul Fathanah Mustamin[3], Yuslena Sari[4], Andreyan Rizky Baskara[5], Eka Setya Wijaya[6], Muhammad Alkaff[7], M.Renald Abdi[8]

Department of Information Technology, Lambung Mangkurat University, Banjarmasin, Indonesia[1, 3, 4, 5, 6, 8]
Department of Environmental Science, Lambung Mangkurat University, Banjarmasin, Indonesia[2]
Department of Computer Science, King Abdulazis University, Jeddah, Saudi Arabia[7]

***Abstract*—Tourism is a vital sector that contributes significantly to Indonesia's economic growth. However, despite its great potential, the sector faces challenges in the application of information technology, as seen in the Go-Klotok application in Banjarmasin City which has not been well received by tourists. Therefore, it is important to understand the factors that influence the acceptance of information technology in river tourism to improve the tourist experience and support the growth of the sector. This study aims to develop a model of technology acceptance and utilization in river tourism in South Kalimantan. To that end, this study modifies four main models, namely the Tourism Web Acceptance Model (T-WAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the E-Tourism Technology Acceptance Model (ETAM), and The DeLone and McLean Model. This research identifies and analyzes various factors that influence technology acceptance in the context of river tourism. The research method uses a hybrid SEM-ANN approach, where Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to analyze the relationship between variables, while Artificial Neural Network (ANN) captures more complex data patterns. Data analysis in this study used the Hybrid SEM-ANN method with the SmartPLS application and the IBM SPSS Statistics 27 application. The hypotheses of this study were 14 hypotheses and 9 hypotheses were accepted. The results of the analysis of 471 respondents show that Social Influence, Perceived Benefits, and Information Quality significantly influence user intention to use information technology services, with Social Influence as the most dominant factor.**

Keywords—River tourism; technology acceptance; TWAM; E-TAM; hybrid SEM-ANN

I. Introduction

Tourism is widely recognized as a crucial driver of economic growth, especially in developing countries where it can have a transformative impact on local economies. Indonesia, as one of the world's largest archipelagic nations, is no exception [1]. Tourism contributes significantly to the country's GDP and is continuously evolving to adapt to global trends. According to the World Travel & Tourism Council (WTTC), the tourism sector's contribution to Indonesia's GDP reached IDR 1,050.38 trillion in 2019, illustrating the vital role tourism plays in Indonesia's economy. Despite the setbacks caused by the COVID-19 pandemic, which led to a 19.6% reduction in this sector, projections are optimistic. The industry is expected to recover, with contributions projected to rise to IDR 1,827.79 trillion by 2034 [2]. This resurgence points to the enormous potential of Indonesia's tourism industry, particularly in niche markets such as eco-tourism, cultural tourism, and river tourism, which offer unique experiences to both domestic and international visitors.

Indonesia's diverse cultural and natural landscapes provide countless tourism opportunities, from its pristine beaches and majestic volcanoes to its rich heritage and vibrant cities. One area that stands out for its unique offerings is South Borneo, specifically the city of Banjarmasin, often referred to as the "City of a Thousand Rivers." The region's geography, characterized by a vast network of rivers, offers a distinctive form of tourism: river-based tourism [3], [4]. River tourism in Banjarmasin is renowned for its floating markets, where traders sell local produce directly from boats, and for the river cruises that allow tourists to explore local life along the riverbanks. Another popular attraction is the klotok boat, a traditional vessel that carries tourists through the waterways, providing a glimpse into the region's cultural and historical richness.

The importance of river tourism to South Borneo's economy cannot be overstated. It not only serves as a key attraction for tourists but also plays a pivotal role in preserving local culture and traditions. River tourism contributes significantly to employment, from boat operators to local vendors, and helps sustain the communities that rely on these waterways for their livelihoods. However, like many other sectors, river tourism has not been immune to the global shift towards digitalization. As tourists increasingly expect convenience and efficiency, the tourism sector must adapt to these changing expectations by integrating technology into its services [5], [6].

In response to these trends, local governments and tourism stakeholders in South Borneo have initiated various efforts to improve the infrastructure and services associated with river tourism. These efforts include the development of technology- based services aimed at enhancing the tourist experience. For example, the introduction of the Go-Klotok app in 2018 was intended to simplify the process of booking klotok rides online, offering tourists a more convenient and efficient way to explore the region's rivers [7]. In addition, several initiatives have been launched to improve public facilities such as rest areas, public toilets, and parking spaces to make river tourism more accessible and comfortable for visitors. The government also continues to add more klotok boats to its fleet, increasing the capacity for river tours and catering to the growing number of tourists.

However, despite these efforts, the integration of information technology into river tourism in South Borneo has encountered significant challenges. While the Go-Klotok app was intended to revolutionize the booking process, it has struggled with low adoption rates. A survey conducted by the local government found that only 10% of tourists used the app to book their boat rides, with the vast majority opting for traditional booking methods at the terminal. Moreover, interviews with klotok operators and tourists revealed that many were unaware of the app's existence, and those who did use it found it difficult to navigate [7]. Tourists expressed a preference for purchasing tickets in person, citing ease of use and a desire for face-to-face interaction as reasons for their reluctance to embrace the app. Some tourists, however, did acknowledge the potential benefits of an online booking system, particularly as a way to avoid long lines during peak tourist seasons.

In light of these challenges, it is evident that while technology has the potential to enhance river tourism services in South Borneo, there are barriers to its widespread acceptance. The failure of the Go-Klotok app, despite significant financial investment, highlights the importance of understanding the factors that influence tourists' acceptance of technology in this context [7]. In the tourism industry, user acceptance of technology is often shaped by factors such as perceived ease of use, perceived usefulness, trust, and familiarity with the technology. Previous research on technology adoption in tourism has identified these factors as critical determinants of whether tourists will embrace new digital solutions. However, in the context of river tourism in South Borneo, where cultural and logistical factors play a significant role, there is a need for further research to uncover the specific factors that influence user acceptance of technology.

This study aims to address this gap by developing a comprehensive model for understanding the acceptance and use of information technology in river tourism services in South Borneo. To achieve this, the research employs a hybrid approach that combines Structural Equation Modeling (SEM) with Artificial Neural Networks (ANN). SEM will be used to analyze the relationships between key variables, while ANN will enhance the accuracy of the results by capturing non-linear relationships that SEM may overlook [8], [9], [10]. The study draws on established theoretical frameworks, including the Tourism Web Acceptance Model (T-WAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the E-Tourism Technology Acceptance Model (ETAM), to identify the key factors that influence tourists' acceptance of technology in the context of river tourism.

The data for this research will be collected through questionnaires distributed to a diverse range of stakeholders, including tourists, tourism managers, and local authorities involved in river tourism in South Borneo. The questionnaires will capture information on tourists' experiences with existing digital services, their perceptions of the usefulness and ease of use of these services, their trust in the technology, and their overall attitudes toward using technology for tourism purposes. This data will then be analyzed using the SEM approach to build a structural model that explains the relationships between these factors. ANN will be used to refine the model and improve the predictive accuracy of the results.

By integrating these methodologies, the research aims to develop a robust model that can explain the factors influencing the acceptance and use of technology in river tourism services. The findings of this study are expected to provide valuable insights for tourism stakeholders in South Borneo, helping them to develop more effective digital services that meet the needs of modern tourists. Furthermore, the study will contribute to the broader theoretical understanding of technology acceptance in the tourism industry, offering a model that can be applied to other contexts within Indonesia and beyond.

In conclusion, the study is expected to make significant contributions to both theory and practice. By identifying the key factors that influence tourists' acceptance of technology in river tourism, the research will provide practical recommendations for improving digital services in South Borneo. At the same time, the use of a hybrid SEM-ANN approach represents an innovative methodological contribution to the study of technology acceptance, offering a new way to analyze complex relationships between variables. Ultimately, this research aims to support the development of more user-friendly and effective technology solutions for the tourism sector, helping to ensure that river tourism in South Borneo can continue to thrive in the digital age.

The remainder of this paper is organized as follows. Section II presents the research design and methodology, including the conceptual framework, population and sample selection, and data analysis techniques. Section III details the research model and hypotheses. Section IV reports and analyzes the results, including validity and reliability tests, structural model assessment, and ANN testing. Section V discusses the implications of the findings in light of existing literature. Section VI concludes the paper with key takeaways, theoretical contributions, practical recommendations, and directions for future research.

II. Related Works

Technology acceptance in tourism has been extensively studied, particularly in the domains of smart tourism, mobile applications, and online booking systems. Several models have been developed to understand user behavior and attitudes toward digital tourism services, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2), the E-Tourism Technology Acceptance Model (ETAM), and the DeLone and Tourism Web Acceptance Model (T-WAM).

TAM emphasizes perceived usefulness and perceived ease of use as key determinants of technology adoption [11]. This model was later extended by Venkatesh et al. through UTAUT and UTAUT2, incorporating constructs such as social influence, performance expectancy, facilitating conditions, and hedonic motivation [12]. While these models are widely applied across technology domains, their generic structure limits their contextual relevance to niche tourism sectors such as river tourism.

In the tourism sector, Tan et al. [13], and Ukpabi and Karjaluoto [14], investigated mobile application use and found that mobile usability, trust, and security are significant predictors of technology adoption. However, these studies focus predominantly on urban or mainstream tourism contexts, overlooking unique characteristics of localized tourism ecosystems such as those found in South Kalimantan.

To address tourism-specific needs, models like the Tourism Web Acceptance Model (T-WAM) and ETAM were developed, incorporating constructs tailored to tourism behavior, including interactivity, trust in service providers, and information quality. These models offer greater relevance but are rarely applied to river-based or traditional tourism systems, where digitalization efforts often face resistance due to entrenched social and cultural practices.

Recent advances in modeling techniques, particularly the integration of Structural Equation Modeling (SEM) with Artificial Neural Networks (ANN), have been employed to improve the explanatory power of technology acceptance research. Barua and Barua [8], for instance, applied a SEM-ANN hybrid to analyze mobile health adoption among Rohingya refugees, while Akour et al. [9] used the same method to assess metaverse adoption in educational institutions. These approaches allow for more accurate modeling of nonlinear behavioral patterns, which conventional SEM alone may fail to capture.

Despite these developments, studies focusing specifically on river tourism technology adoption remain scarce. Platforms such as Go-Klotok, developed by local governments, have seen limited uptake despite heavy investment. This reflects the need to incorporate cultural, infrastructural, and behavioral dimensions into the modeling of technology acceptance in these settings.

III. Materials and Methods

A. Research Design

The conceptual framework provides an overview of the steps taken in this research, which aims to develop a model for technology acceptance and utilization in river tourism, particularly in South Borneo. With the growing role of technology in tourism, understanding the factors influencing its adoption is crucial. This study integrates the Tourism Web Acceptance Model (T-WAM), Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and E-Tourism Technology Acceptance Model (ETAM) to identify and analyze key factors affecting users' acceptance and use of technology in river tourism.

This research employs a hybrid method using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Artificial Neural Networks (ANN). PLS-SEM is used to analyze the relationships between variables, while ANN helps capture complex patterns to enhance model accuracy. This approach aims to provide insights and recommendations for improving technology-based river tourism services.

B. Population and Sample

The target population consists of smartphone users in South Kalimantan aged 20 to 49 years, as this group exhibits a high level of smartphone usage: 75.95% for ages 20 to 29 and 68.34% for ages 30 to 49, according to GoodStats [15]. The sample will include individuals knowledgeable about information technology and mobile applications, ensuring that the data collected is representative and pertinent to the study's focus on the use of technology in tourism services.

The overall population for this study encompasses all South Borneo residents aged 20 to 49, totaling 1,973,864 individuals [16]. This age range was selected based on significant smartphone usage statistics, indicating that the majority of users fall within these age groups. To determine the necessary sample size, Slovin's formula was applied, resulting in an approximate sample size of 400 respondents [17].

This sample will represent the active smartphone users in the region, including both tourists and tourism managers. By establishing this sample size, the research aims to ensure that the collected data accurately reflects the role of information technology in tourism in South Borneo.

C. Data Collection Methods

In this study, data collection is conducted using purposive sampling, a non-probability sampling method chosen for its ability to select samples with specific characteristics relevant to the research. The target sample includes residents of South Kalimantan who frequently use smartphones, particularly individuals aged 20 to 49 years, as this age group demonstrates high smartphone usage. According to GoodStats, smartphone usage is most dominant among those aged 20 to 29 (75.95%) and 30 to 49 (68.34%), with lower rates observed in the 50-79 age group (50.79%) [15].

The questionnaire is distributed online via Google Forms, selected for its efficiency in reaching a large sample. This digital approach allows for quicker distribution and easier access for participants, as respondents can complete the survey anytime and anywhere using their smartphones or computers. Google Forms also facilitates organized data collection and simplifies analysis.

The demographic information collected in this study includes age, gender, occupation, domicile, last education level, frequency of tourism visits in South Kalimantan, and frequency of using tourism-related applications or websites specific to the region. The diverse demographic data ensures that the sample is representative of the population, aiding in the investigation of technology acceptance and utilization in river tourism services.

D. Data Analysis Technique

Data analysis and hypothesis testing are conducted to examine the relationships among the variables defined in the study. This process is crucial for understanding how these variables interact and influence one another. Given the complexity of the research questions and the objectives of this study, a Hybrid SEM-ANN (Structural Equation Modeling - Artificial Neural Network) method is employed. This approach combines the strengths of both Structural Equation Modeling, which allows for the assessment of complex relationships between observed and latent variables, and Artificial Neural Networks, which can capture nonlinear patterns in the data. By utilizing this hybrid method, the analysis aims to provide deeper and more comprehensive insights into the relationships among the variables, ultimately enhancing the validity and reliability of the research findings.

E. Research Hypothesis and Model

This sub-chapter presents the findings of the study, focusing on the relationships between key variables as outlined in the proposed hypotheses. Each hypothesis is discussed based on the data collected and analyzed, offering insights into how various factors influence the acceptance and use of information technology in river tourism services.

The relationship between Platform Quality and Design (DP) and Perceived Ease of Use (PEOU) suggests that a well-designed platform enhances user experience and ease of use. High-quality designs with intuitive navigation and user-friendly interfaces make platforms easier to navigate, leading to a higher perception of ease of use. Previous research supports this link, showing that good design improves usability and satisfaction [17], [18]. Therefore, the hypothesis is:

H1: Quality and Design of the Platform (DP) positively affect Perceived Ease of Use (PEOU).

Security is vital in reducing perceived risk for e-tourism platforms. Higher security measures protect user data and build trust, which in turn lowers perceived risk. Studies show that strong security enhances user confidence and decreases perceived risk (Kim et al., 2011; Tussyadiah et al., 2019) [20]. Users feel safer with robust security features, such as two-factor authentication, which lessens their risk concerns [19]. Therefore, the hypothesis is:

H2: Security (SC) negatively affects Perceived Risk (PR).

Mobile applications that are well-designed and efficient can enhance users' perceptions of facilitating conditions by improving accessibility and ease of use. This hypothesis suggests that a high-quality mobile app will positively influence the perceived supporting conditions, such as access to resources and technical support. Prior research, such as studies by Tan et al. (2017) and Ukpabi & Karjaluoto (2017), supports the idea that effective mobile applications enhance user experience and adoption of e-tourism platforms [13], [14]. Interviews with tourism operators confirm that reliable and functional mobile apps positively impact their perception of supporting conditions. Therefore, the hypothesis is:

H3: Mobile Applications (MA) positively affect Facilitating Conditions (FC).

Reliable and efficient online payment systems are crucial for improving users' perceptions of facilitating conditions in e- tourism platforms. This hypothesis posits that effective online payment methods enhance users' perceptions of supporting conditions, such as system reliability and customer support. Prior research by Slade et al. (2015) indicates that secure and user-friendly payment systems boost user trust and satisfaction [21]. Interviews with tourists confirm that robust online payment options, with strong data protection and support, positively influence their perception of facilitating conditions. Therefore, the hypothesis is:

H4: Online Payment (OP) positively affects Facilitating Conditions (FC).

Perceived Ease of Use (PEOU) influences Perceived Usefulness (PU) because technologies that are easy to use are often perceived as more beneficial. When users find a technology simple and user-friendly, they are more likely to view it as useful. Research by Davis (1989), and Venkatesh et al. (2003) supports this relationship, showing that ease of use generally enhances perceived usefulness [11], [12]. Interviews with klotok operators confirm that they prefer applications with simple interfaces, which facilitate their daily operations and increase the perceived utility of the technology. Therefore, the hypothesis is:

H5: Perceived Ease of Use (PEOU) positively affects Perceived Usefulness (PU).

Perceived Usefulness (PU) is crucial in shaping users' intention to use technology. When users perceive significant benefits from a technology, they are more likely to intend to use it. Research by Davis (1989), and Venkatesh et al. (2003) supports this, showing that higher perceived benefits correlate with stronger adoption intentions [11], [12]. Interviews with stakeholders reveal that users are more inclined to use applications that they find useful, such as those providing ticket booking and route information. This indicates that greater perceived usefulness leads to a stronger intention to use the technology. Therefore, the hypothesis is:

H6: Perceived Usefulness (PU) positively affects the Intention to Use River Tourism IT Services (INT).

Facilitating Conditions (FC) include infrastructure, resources, and support available for technology use. This factor impacts the Intention to Use River Tourism IT Services (INT) because adequate support and resources increase users' willingness to adopt technology. According to the UTAUT model (Venkatesh et al., 2003), good facilitating conditions enhance the intention to use technology [12]. Previous studies have shown that robust infrastructure and responsive support positively correlate with technology adoption. Interviews with tourism operators confirm that reliable internet access and effective customer support are crucial for their continued use of mobile applications [12]. Therefore, better facilitating conditions are expected to increase users' intention to use the technology. Therefore, the hypothesis is:

H7: Online Payment (OP) positively affects Facilitating Conditions (FC).

Performance Expectancy (PE) reflects users' belief that technology will help achieve desired outcomes. This factor impacts the Intention to Use River Tourism IT Services (INT) because if users expect high performance from the technology, they are more likely to intend to use it. According to the UTAUT model (Venkatesh et al., 2003), high performance expectancy increases users' intention to adopt technology [12]. Previous research supports this, showing that strong expectations for performance are positively related to usage intentions. Interviews reveal that stakeholders expect high performance in terms of speed and accuracy from river tourism applications, which influences their intention to use the technology [12]. Therefore, the hypothesis is:

H8: Performance Expectancy (PE) positively affects the Intention to Use River Tourism IT Services (INT).

Trust (TR) reflects users' confidence in the security and reliability of technology or services, significantly influencing their intention to use river tourism IT services (INT). High levels of trust encourage users to engage with the technology. Research by Gefen et al. (2003), highlights that trust plays a crucial role in the intention to use these services [22]. Trust is fundamental to technology adoption; without it, users may hesitate to embrace technology despite its clear benefits. Prior studies have established a strong connection between trust and users' intentions to adopt technology. For instance, Gefen et al. (2003) found that trust closely correlates with the intent to use technology. This study assumes that trust is a key factor in shaping users' willingness to engage with technology, particularly in contexts involving online transactions or personal data [22]. Therefore, the hypothesis is:

H9: Trust (TR) positively affects the Intention to Use River Tourism IT Services (INT).

Perceived Risk reflects users' perception of potential losses or dangers associated with using technology. This variable negatively influences the intention to use river tourism IT services (INT); as perceived risk increases, users' intent to adopt the technology decreases. Research by Featherman and Pavlou (2003) indicates that perceived risk is a major barrier to the adoption of new technologies [23]. Users who perceive high risk are likely to avoid or delay using the technology. Previous studies support the notion that Perceived Risk is negatively related to the intention to use technology, with Featherman and Pavlou (2003) finding that perceived risk reduces users' intent to engage with technology [23]. The researcher believes that perceived risk will adversely impact the intention to use technology. If users feel there are high risks, such as data loss or security threats, they may hesitate or postpone their use of the technology. Therefore, the hypothesis is:

H10: Perceived Risk (PR) negatively affects the Intention to Use River Tourism IT Services (INT).

Perceived Benefits (PB) reflects users' perceptions of the advantages or added value derived from using technology. This variable positively influences the intention to use river tourism IT services (INT); as perceived benefits increase, so does the intention to adopt the technology. Research by Venkatesh et al. (2012), demonstrates that Perceived Benefits are a significant predictor of usage intention [12]. When users recognize tangible advantages from technology, they are more motivated to use it. Previous studies have shown a positive correlation between Perceived Benefits and the intention to adopt technology, with Venkatesh et al. (2012), finding that perceived advantages directly influence users' intent to adopt. The researcher assumes that the extent to which users believe technology provides real benefits will enhance their intention to use it [12]. Therefore, the hypothesis is:

H11: Perceived Benefits (PB) positively affects the Intention to Use River Tourism IT Services (INT).

Social Influence is a crucial factor affecting individuals' decisions to adopt technology. In river tourism, the encouragement from friends, family, or respected figures can significantly impact a person's intention to use IT services. When individuals perceive support from those around them, they are more likely to strengthen their intent to engage with these technologies. According to Venkatesh et al. (2003), social influence is vital in determining usage intentions, particularly when significant others endorse the technology [12]. Many respondents indicated they often rely on recommendations from peers when choosing tourism platforms. Community discussions about technology also play a role in shaping their decisions. Therefore, the hypothesis is:

H12: Social Influence (SI) positively affects the Intention to Use River Tourism IT Services (INT).

Information Quality is a crucial factor influencing individuals' decisions to adopt technology. Accurate, reliable, and relevant information helps potential users understand the benefits of technology and encourages their intention to use it. In the context of river tourism IT services, high-quality information provided through platforms (such as apps, websites, or social media) can increase interest among tourists or locals. Effective information includes clear service descriptions, user reviews, offered features, and data security assurances. The DeLone and McLean model (2014) highlights that information quality is vital for the success of information systems and impacts technology usage intentions. Users tend to hesitate if the presented information is incomplete or outdated. Thus, high- quality information not only enhances user confidence but also directly influences their intention to use these services [24]. Therefore, the hypothesis is:

H13: Information Quality (IQ) positively affects the Intention to Use River Tourism IT Services (INT).

Service Quality is a critical aspect of any interaction involving technology and users. In the context of tourism, good service quality—characterized by user-friendly, responsive, and accessible platforms—is believed to enhance users' intentions to continue using those services. When users perceive the services as efficient, reliable, and aligned with their needs, they are more likely to engage with them in the future. According to the DeLone and McLean Model (2014), service quality is one of three key factors influencing the success of information systems, alongside information quality and system quality. This model emphasizes that high service quality, particularly in terms of technical support and response time, directly affects user satisfaction and increases the intention to use technology [24]. From previous research, it can be concluded that when tourists feel that the technology systems, they use provide prompt, responsive, and effective support, they are more likely to feel comfortable and confident in using those services again. Therefore, the hypothesis is:

H14: Service Quality (SQ) positively affects the Intention to Use River Tourism IT Services (INT).

Following the hypotheses, it is crucial to integrate these relationships into a coherent research model that illustrates the connections between factors influencing the intention to use river tourism IT services as shown in Fig. 1. This model will provide a structured framework to clarify how variables such as perceived benefits, trust, social influence, and service quality interact with users' intentions.

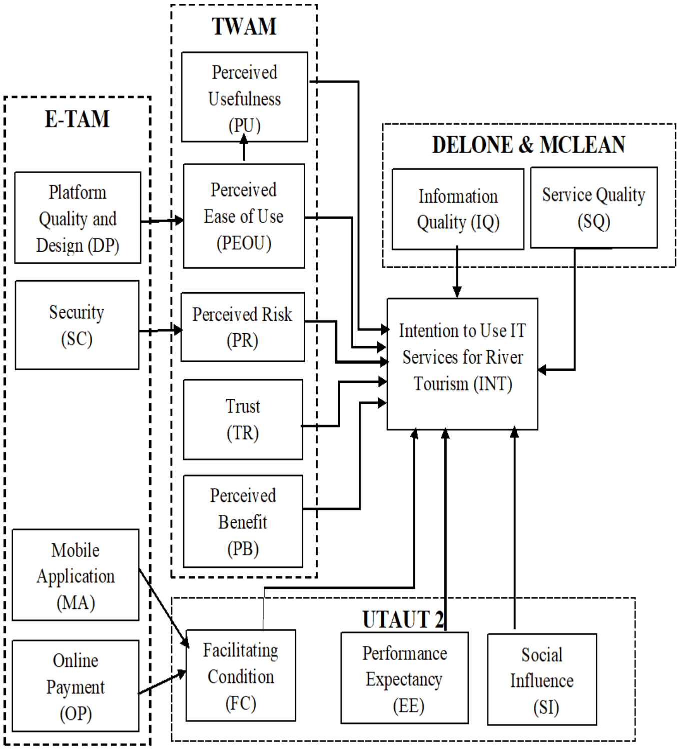

Fig. 1. Research model.

IV. Result and Discussion

A. Data Acquisition

The data collection in this study presents a comprehensive overview of the data obtained from the questionnaire based on a predetermined sample. The research data includes two main aspects, namely the demographics of respondents and the results of the research model analysis. Demographic aspects include information on age, gender, occupation, domicile, education level, as well as the frequency of tourist visits and the use of river tourism-related applications. Data collection was conducted online through social media platforms such as WhatsApp, Instagram, Telegram, Facebook, and X (Twitter), with a total of 471 respondents, where only data that was filled in completely by respondents was considered valid. The demographics of the respondents show a distribution that dominates young age, with the majority working as students or college students, and the domicile of respondents is concentrated in the Banjarmasin and Banjarbaru regions.

B. Validity and Reliability

The measurement model or outer model describes the relationship between latent variables and their indicators. This model serves to measure the validity and reliability of each indicator. Evaluation of the measurement model includes three main steps, namely convergent validity, discriminant validity, and composite reliability tests.

The convergent validity test assesses the ability of indicators to reflect the construct or latent variable being measured. This test is done by checking the outer loadings value. Indicators are considered valid if the outer loadings value is more than 0.70, which indicates that the indicator can explain more than 50% of the variance of the measured construct. This convergent validity test consists of two main components, namely Factor Loading and Average Variance Extracted (AVE). To achieve sufficient convergent validity, the AVE value of each latent variable must be more than 0.5, indicating that the latent construct is able to explain more than half of the variation in its indicators.

The discriminant validity test aims to ensure that a latent variable has a stronger relationship with its indicators than other latent variables. This test is carried out using two methods, namely the Fornell-Larcker Criterion and Cross Loadings. In Cross Loadings, discriminant validity is achieved if the indicator load on the related latent variable is greater than the load on other variables. Meanwhile, the Fornell-Larcker Criterion states discriminant validity when the square root value of the AVE of each variable is greater than the correlation with other variables. In other words, discriminant validity is considered good if the AVE square root of each exogenous construct exceeds the correlation between constructs.

Reliability tests are carried out to determine the consistency of the model, evaluating the extent to which variations in model results are caused by variations in the original data and not by measurement errors, for example from respondents' misunderstanding of questions. Reliability is measured through two main indicators, namely composite reliability and Cronbach's Alpha. If the composite reliability value is more than 0.70, the latent variable is considered to have good reliability. Cronbach's Alpha is also used as a measure of reliability, with a rating scale: 0.81 to 1.00 (highly reliable), 0.61 to 0.80 (reliable), 0.42 to 0.60 (moderately reliable), 0.21 to 0.41 (unreliable), and 0.00 to 0.20 (highly unreliable).

The final results of validity and reliability testing show that there are eighteen (18) indicators that do not meet the critical value, so they are declared invalid. Invalid indicators include DP3 (Platform Quality and Design), MA4 (Mobile Application), OP2 and OP3 (Online Payment), PEOU2 (Perceived Ease of Use), PU2 and PU3 (Perceived Usability), FC4 (Supporting Conditions), PE1 and PE4 (Performance Expectations), TR1 and TR3 (Trust), PB4 (Perceived Benefits), SI2 (Social Influence), IQ2 (Information Quality), SQ3 and SQ4 (Service Quality), and INT2 (Intention to Use IT Services for River Tourism). The final results of outer loading are in Table I and reliability measurements are in Table II.

TABLE I FINAL RESULT OF OUTER LOADINGS

Variable	Indicator	Outer Loadings
Platform Quality and Design (DP)	DP1	0,779
	DP2	0,778
	DP4	0,800
Security (SC)	SC1	0,773
	SC2	0,753
	SC3	0,750
	SC4	0,715
Mobile Application (MA)	MA1	0,750
	MA2	0,745

Variable	Indicator	Outer Loadings
	MA3	0,782
Online Payment (OP)	OP1	0,804
	OP4	0,854
Perceived Ease of Use (PEOU)	PEOU1	0,773
	PEOU3	0,812
	PEOU4	0,707
Perceived Usefulness (PU)	PU1	0,824
	PU4	0,840
Facilitating Conditions (FC)	FC1	0,812
	FC2	0,738
	FC3	0,794
Performance Expectancy (EE)	PE2	0,838
	PE3	0,787
Trust (TR)	TR2	0,873
	TR4	0,832
Perceived Risk (PR)	PR1	0,773
	PR2	0,804
	PR3	0,762
	PR4	0,813
Perceived Benefit (PB)	PB1	0,759
	PB2	0,753
	PB3	0,801
Social Influence (SI)	SI1	0,805
	SI3	0,775
	SI4	0,707
Information Quality (IQ)	IQ1	0,819
	IQ3	0,783
	IQ4	0,741
Service Quality (SQ)	SQ1	0,870
	SQ2	0,757
Intention to Use IT Services for River Tourism (INT)	INT1	0,810
	INT3	0,786
	INT4	0,759

TABLE II REALIBILITY MEASUREMENT RESULTS

Variable	Composite Reliability	Cronbach's Alpha
Platform Quality and Design (DP)	0,829	0,690
Security (SC)	0,836	0,738
Mobile Application (MA)	0,803	0,633
Online Payment (OP)	0,815	0,548
Perceived Ease of Use (PEOU)	0,809	0,646
Perceived Usefulness (PU)	0,818	0,555
Facilitating Conditions (FC)	0,825	0,682
Performance Expectancy (PE)	0,795	0,487
Trust (TR)	0,842	0,627
Perceived Risk (PR)	0,868	0,804
Perceived Benefit (PB)	0,815	0,659
Social Influence (SI)	0,807	0,644

C. Structural Model and Hypothesis Testing

The inner model, or structural model, is used to assess the predictive ability of the model and the relationship between variables by seeing how well the independent variables can explain the dependent variable in the model. Some of the key criteria in evaluating the structural model include the R-square value and level, as well as the significance of the path coefficients. A high R-square value is required for the main target variable, because the higher the R-square value, the greater the ability of the model to explain variations in the dependent variable. The R-square rating scale is as follows: ⩾ 0.67 is considered good, 0.66 to 0.33 moderate, and 0.32 to 0.19 weak.

In this research model, the Supporting Conditions (FC) variable has an R-square value of 0.361, which indicates that the Mobile Application (MA) and Online Payment (OP) variables together explain 36.1% of the variation in Supporting Conditions (FC), and are categorized as a moderate inner model. The variable Intention to Use River Tourism IT Services (INT) has an R-square value of 0.411, which means that the variables of Perceived Usefulness (PU), Supporting Conditions (FC), Performance Expectations (PE), Trust (TR), Perceived Risk (PR), Perceived Benefits (PB), Social Influence (SI), Information Quality (IQ), and Service Quality (SQ) collectively explain 41.1% of the variation in Intention to Use River Tourism IT Services (INT), and this is also included in the moderate category.

The R-square value for the Perceived Ease of Use (PEOU) variable is 0.270, which indicates that the Platform Quality and Design (DP) variable explains 27% of the variation in Perceived Ease of Use (PEOU), so it is categorized in the weak model. Meanwhile, the R-square value of Perceived Risk (PR) of 0.109 indicates that Security (SC) only explains 10.9% of the variation in Perceived Risk (PR). Since this value is below the minimum limit of 0.190 on the R-square scale, Risk Perception (PR) is categorized as invalid or not explaining enough variation in the model.

Finally, the R-square value for Perceived Usefulness (PU) of 0.288 indicates that Perceived Ease of Use (PEOU) explains 28.8% of the variation in Perceived Usefulness (PU), which is categorized as weak. The complete R-square results can be seen in Table III below.

TABLE III R-SQUARE VALUE

Variable	R-square	Description
FC	0,361	Moderate
INT	0,411	Moderate
PEOU	0,270	Weak
PR	0,109	Not Enough
PU	0,288	Weak

The P-Value calculation is used as the basis for PLS-SEM testing. The bootstrapping method is the most commonly applied technique for estimating standard errors in PLS-SEM. Hypothesis testing is done by considering the Original Sample value, T-Statistic, and P-Value. The conclusion regarding the acceptance or rejection of the hypothesis can be determined based on the T-Statistics value. The critical values commonly used to test the significance of path coefficients are 1.65 (10% significance level), 1.96 (5% significance level), and 2.57 (1% significance level). The choice of significance level depends on the purpose and field of study; generally, a 10% significance level is assumed in exploratory research, while a 5% level is used in marketing research.

In this study, T-Statistics values greater than 1.96 (5% significance level) indicate that the hypothesis is accepted, while values below 1.96 indicate that the hypothesis is rejected. In addition, the P-Value can also determine the acceptance of the hypothesis; the hypothesis will be accepted if the P-Value is less than 0.05. This study involved 14 variables and 471 respondents, with the error rate set at 5% or 0.050. The results of hypothesis testing using the bootstrapping method in SmartPLS can be seen in Table IV.

TABLE IV RELIABILITY MEASUREMENT RESULTS

Hypothesis	T-Statistics (|O/STDEV|)	P-Value	Description
H1: DP → PEOU	10.652	0.000	Hypothesis Accepted
H2: SC → PR	5.707	0.000	Hypothesis Accepted
H3: MA → FC	7.979	0.000	Hypothesis Accepted
H4: OP → FC	7.244	0.000	Hypothesis Accepted
H5: PEOU → PU	11.659	0.000	Hypothesis Accepted
H6: PU → INT	1.146	0.252	Hypothesis Rejected
H7: FC → INT	1.926	0.054	Hypothesis Rejected
H8: PE → INT	1.555	0.120	Hypothesis Rejected
H9: TR → INT	1.622	0.105	Hypothesis Rejected
H10: PR → INT	3.392	0.001	Hypothesis Accepted
H11: PB → INT	2.022	0.043	Hypothesis Accepted
H12: SI → INT	4.318	0.000	Hypothesis Accepted
H13: IQ → INT	2.288	0.022	Hypothesis Accepted
H14: SQ → INT	1.196	0.232	Hypothesis Rejected

D. Structural Model and Hypothesis Testing

Importance-Performance Map Analysis (IPMA) was used to evaluate the factors influencing Intention to Use River Tourism IT Services (INT) with a PLS-SEM approach. IPMA enables a deeper understanding of the PLS-SEM model by assessing alternative path coefficients as measures of importance. In addition, IPMA includes latent constructs as well as the performance of each variable tested. In this study, 14 main factors, namely Platform Quality and Design (DP), Security (SC), Mobile Application (MA), Online Payment (OP), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Supporting Conditions (FC), Performance Expectations (PE), Trust (TR), Perceived Risk (PR), Perceived Benefits (PB), Social Influence (SI), Information Quality (IQ), and Service Quality (SQ), were measured based on their importance and performance. Table V is the result of Importance-Performance Map Analysis as follows.

TABLE V IMPORTANCE-PERFORMANCE MAP ANALYSIS (IPMA)

Variable	Importance	Performance
DP	0.017	84.072
SC	-0.038	84.781
MA	0.042	84.722
OP	0.038	82.288
PEOU	0.033	83.558
PU	0.062	84.004
FC	0.112	83.055
PE	0.090	84.063
TR	0.080	84.568
PR	-0.114	83.567
PB	0.128	83.311
SI	0.251	79.603
IQ	0.126	84.931
SQ	0.064	84.686

Based on the IPMA results, the variable with the highest importance is SI, followed by PB, IQ, FC, PE, TR, SQ, PU, MA, OP, PEOU, DP, SC, and PR have the lowest importance. For the highest performance, the variable with the highest value is IQ, followed by SC, MA, SQ, TR, DP, PE, PU, PR, PEOU, PB, FC, OP, and SI are in the lowest order. The IPMA results are visualized in the form of a graph, where the horizontal axis represents the importance value (Total Effects) of the various influencing factors, on a scale of 0 to 1. Meanwhile, the vertical axis shows the performance of these factors on a scale from 0 to 100.

E. Artificial Neural Network (ANN) Testing

Artificial Neural Network (ANN) testing was conducted to strengthen the results of the PLS-SEM analysis and assess the relative importance of the significant factors generated by SEM. The results of SEM analysis showed that all hypothesized relationships were accepted, while ANN was used to validate these results, focusing on variables that were considered important based on PLS-SEM. In this study, variables such as DP, IQ, MA, OP, PEOU, PR, SC, SI, and PB were tested using the ten-fold cross-validation method with one-hidden layer to prevent overfitting. The application used was IBM SPSS Statistics 27.

ANNs produce performance metrics such as Root Mean Squared Error (RMSE), which measures the average error between the actual value and the resultant value of the ANN. The smaller the RMSE value, the better the model performance. In addition, the importance scores generated by the ANN show how much each variable contributes to the output. Sum of Squared Errors (SSE) values close to zero indicate that the model has a smaller random error component, making the model more suitable for use. The smaller the RMSE value, the higher the accuracy of the ANN model using in Fig. 2.

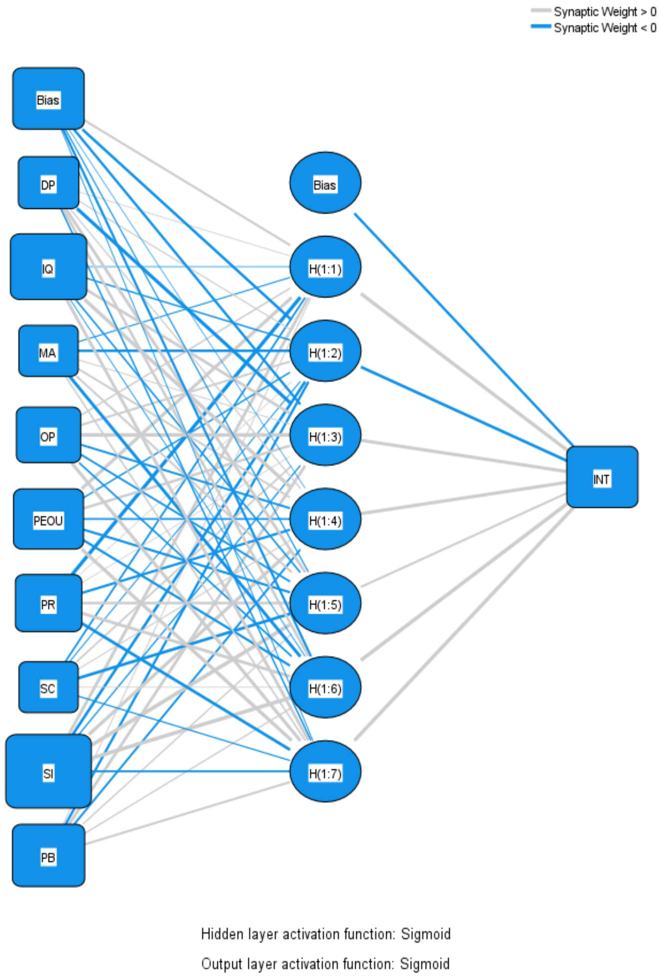

Fig. 2. Artificial neural network (ANN) model.

TABLE VI RMSE VALUE FOR ANN TRAINING AND TESTING

NN	Training			Testing			Total Sample N1 + N2
	N1	SSE	RMSE	N2	SSE	RMSE	
1	383	4,076	0,103	88	0,799	0,095	471
2	367	5,236	0,119	104	1,349	0,114	471
3	389	4,057	0,102	82	0,966	0,109	471
4	375	4,154	0,105	96	0,834	0,093	471
5	369	3,924	0,103	102	1,067	0,102	471
6	384	4,089	0,103	87	0,962	0,105	471
7	357	3,919	0,105	114	1,200	0,103	471
8	385	6,191	0,127	86	1,381	0,127	471
9	371	4,021	0,104	100	1,012	0,101	471
10	369	4,221	0,107	102	1,117	0,105	471
Average		4,389	**0,108**		1,069	**0,105**	
Standard Dev.		0,701	0,008		0,187	0,009	

The results from the Artificial Neural Network (ANN) testing in Table VI showed an average RMSE for training (N1) of 0.108 and for testing (N2) of 0.105, with standard deviations of 0.008 and 0.009, respectively. This indicates that the model has a low and consistent error rate, both when training and testing the data. The average SSE value for training was 4.389 and for testing was 1.069, indicating a relatively small amount of squared error. Overall, the ANN model performed well and was stable, with minimal error.

The sensitivity analysis stage was conducted by calculating the importance of each input in the form of a percentage, as shown in Table VII, referred to as the normalized importance. This is obtained by dividing the relative importance value of each input variable by the highest importance value in the ANN model. This process aims to understand how much each variable contributes in influencing the final outcome. This sensitivity analysis also helps to rank the exogenous variables, so that it can be known which ones are the most influential in the model.

TABLE VII SENSITIVITY VALUE

NN	DP	IQ	MA	OP	PEOU	PR	SC	SI
1	0,123	0,678	0,080	0,261	0,458	0,329	0,076	1,000
2	0,645	0,368	0,101	0,382	0,479	0,627	0,099	1,000
3	0,290	0,801	0,151	0,257	0,884	0,492	0,156	1,000
4	0,434	0,851	0,130	0,442	0,410	0,255	0,241	1,000
5	0,217	0,735	0,236	0,389	0,357	0,525	0,189	1,000
6	0,420	0,755	0,106	0,227	0,507	0,309	0,128	1,000
7	0,563	0,475	0,557	0,504	0,221	0,168	0,263	1,000
8	0,281	0,511	0,463	0,369	0,805	0,264	0,172	0,070
9	0,523	0,814	0,213	0,680	0,293	0,422	0,297	1,000
10	0,187	0,739	0,577	0,410	0,112	0,091	0,257	1,000
Average Importance	0,368	0,673	0,261	0,392	0,453	0,348	0,188	0,907
Normalized Importance	41%	74%	29%	43%	50%	38%	21%	100%

F. Discussion of SEM-ANN Results

This study examines the factors that influence the intention to use IT services in river tourism, finding several key findings. Good platform quality and design increase perceived ease of use, making users more comfortable accessing services. Security factors are also significant in reducing perceived risk, indicating the importance of data encryption and strong security systems to increase user trust. Mobile apps play an important role in creating optimal enabling conditions, while secure online payment options support user convenience in digital transactions. While perceived usefulness does not directly affect usage intentions, the benefits of the service must be clearly conveyed to increase interest.

Some factors, such as enabling conditions and performance expectations, were not significant to usage intention. Service providers need to provide realistic information and adequate support to make users feel helpful. User trust, although not significant, should still be built through transparent policies and responsive services. Perceived risk has a negative effect on intention to use, so risk mitigation strategies are important to reduce user concerns. Perceived benefits and social influence proved to be the dominant factors driving usage intention, where recommendations from close people and clear and relevant information can increase interest. Although service quality is not significant, providers should focus on delivering compelling benefits and information to make users more interested in switching to these IT services.

This study tested SEM-based IPMA and ANN-based sensitivity analysis with the results showing that Social Influence (SI), Perceived Benefits (PB), and Information Quality (IQ) are the three most significant independent variables in influencing user intentions. SI has the highest importance value in both methods, 0.251 in IPMA and 0.907 in ANN, indicating that this factor is very important in influencing user decisions, although its performance still needs to be improved. PB, with a value of 0.128 in IPMA and 0.730 in ANN, indicates that users' perceived benefits are also quite influential on their intentions. IQ, with a value of 0.126 in IPMA and 0.673 in ANN, indicates that the quality of information provided by the platform is very important to users. Based on result comparison shown in Table VIII, it shows that the alignment between the two analyses and reinforce the importance of these three variables in driving user intentions.

TABLE VIII COMPARISON OF IMPORTANCE VALUES FOR VARIABLES IN IPMA AND SENSITIVITY ANALYSIS

Variable	IPMA Importance	Sensitivity Analysis Importance
SI	0.251	0,907
PB	0.128	0,730
IQ	0.126	0,673

V. CONCLUSION

This research aims to analyze the factors that influence the acceptance and utilization of information technology in river tourism services in South Kalimantan. The method used is a Hybrid SEM-ANN approach on 471 respondents, which provides an in-depth understanding of the interaction between relevant variables. The results show three main factors that have a significant effect on user intention to use the service, namely Social Influence, Perceived Benefits, and Information Quality. Social Influence has the strongest impact on driving user intentions, followed by Perceived Benefits that strengthen intentions by providing direct benefits from using the service, and Information Quality that provides clarity and certainty in decision-making.

Based on these findings, the study recommends several strategies to increase the adoption of information technology-[22] based river tourism services. Strengthening Social Influence can be done by utilizing social media or digital platforms, through campaigns involving user testimonials, interactions between users, and loyalty programs. Increasing Perceived Benefits can be achieved by adding value-added features, such as service personalization, up-to-date information on routes and river conditions, and easy access to assistance services. On the other hand, Information Quality needs to be maintained by ensuring all information is regularly updated, easy to understand, and accurate, especially regarding river tourism facilities and conditions.

However, this study is not without limitations. First, the data were collected only from users in South Kalimantan, which may limit the generalizability of the findings to other regions or tourism contexts. Second, the model focuses on selected variables, which, although significant, may not capture other potential factors influencing technology adoption in river tourism. Lastly, the cross-sectional nature of the data limits the ability to observe changes in user behavior over time. Future research could address these limitations by expanding the geographical scope, incorporating additional variables, and using longitudinal designs.

The results of this study are expected to serve as a guide for managers and stakeholders in designing IT services that are more effective and in line with user needs, while also encouraging further investigation into broader factors and contexts affecting technology adoption in tourism.

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