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Research Article

# Factors Determining the Behavioral Intention to Use the Geographic Information System for Managing Marine Resources in the Coastal Area of Bandon Bay, Surat Thani Province

**A-Phorn Molee[1*]**

## Abstract

This research emphasizes the examination of factors influencing behavioral intention to use a Geographic Information System (GIS) for coastal marine resource management in Bandon Bay, Surat Thani Province. The study employs a survey research design with a population comprising residents along the Bandon Bay coastline. A sample of 398 participants was selected through simple random sampling using a questionnaire (Cronbach's Alpha = 0.857). The research utilizes an extended the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model with seven factors: Behavioral Intention (BI), Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), and Price Value (PV). Data analysis was conducted by using mean, standard deviation, correlation, and multiple regression analysis.

The findings reveal that Behavioral Intention is the factor with the highest mean level, with an overall mean in the highest category ($\bar{x}$ = 4.623, S.D. = 0.447), followed by Price Value with an overall mean also in the highest category ($\bar{x}$ = 4.612, S.D. = 0.464). The remaining five factors have means in the high category: Social Influence ($\bar{x}$ = 4.474, S.D. = 0.658), Performance Expectancy ($\bar{x}$ = 4.463, S.D. = 0.515), Hedonic Motivation ($\bar{x}$ = 4.376, S.D. = 0.506), Effort Expectancy ($\bar{x}$ = 4.366, S.D. = 0.446), and Facilitating Conditions ($\bar{x}$ = 4.154, S.D. = 0.504), respectively.

The multiple regression analysis results indicate an $AdjR^2$ value of 0.637, accounting for 63.70% of the total variance from five factors. This demonstrates that Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Hedonic Motivation have statistically significant effects. The resulting predictive equation is as follows: BI = 1.463 + 0.540(PE) - 0.126(EE) + 0.200(SI) - 0.042(FC) + 0.088(HM). The findings can be applied to support the development of a geographic information system for managing marine and coastal resources in Bandon Bay, Surat Thani Province. The system development should focus on the factor weights specified in the predictive equation.

**Keywords:** Behavioral Intention; UTAUT2 Model; Geographic Information System; Bandon Bay.

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# การตรวจสอบปัจจัยที่ส่งผลต่อพฤติกรรมความตั้งใจใช้ระบบสารสนเทศภูมิศาสตร์เพื่อการจัดการทรัพยากรทางทะเลชายฝั่งอ่าวบ้านดอน จังหวัดสุราษฎร์ธานี

เอพร โมฬี[2*]

## บทคัดย่อ

การวิจัยเชิงสำรวจนี้เน้นย้ำการตรวจสอบปัจจัยที่ส่งผลต่อพฤติกรรมความตั้งใจใช้ระบบสารสนเทศภูมิศาสตร์เพื่อการจัดการทรัพยากรทางทะเลชายฝั่งอ่าวบ้านดอน จังหวัดสุราษฎร์ธานี การวิจัยนี้ใช้แบบสอบถาม (Cronbach's Alpha = 0.857) เพื่อเก็บรวบรวมจากผู้อยู่อาศัยแนวชายฝั่งทะเลอ่าวบ้านดอน โดยกำหนดขนาดกลุ่มตัวอย่างการวิจัย จำนวน 398 คน ด้วยวิธีสุ่มอย่างง่าย ใช้การขยาย UTAUT2 model จำนวน 7 ปัจจัย คือ พฤติกรรมความตั้งใจ (Behavioral Intention – BI), การคาดหวังผลการใช้งาน (Performance Expectancy – PE), การคาดหวังด้านความพยายาม (Effort Expectancy – EE), อิทธิพลทางสังคม (Social Influence – SI), เงื่อนไขสนับสนุน (Facilitating Conditions – FC), แรงจูงใจด้านความเพลิดเพลิน (Hedonic Motivation – HM) และมูลค่าด้านราคา (Price Value – PV) การวิเคราะห์ข้อมูลด้วยค่าเฉลี่ย ส่วนเบี่ยงเบนมาตรฐาน การวิเคราะห์ความสัมพันธ์ และการวิเคราะห์การถดถอยเชิงพหุ

ผลการวิจัยพบว่า พฤติกรรมความตั้งใจเป็นปัจจัยที่มีระดับค่าเฉลี่ยสูงสุดและมีค่าเฉลี่ยรวมอยู่ในระดับมากที่สุด ($\bar{x}$ = 4.623, S.D. = 0.447) รองลงมาคือ มูลค่าด้านราคา มีค่าเฉลี่ยรวมอยู่ในระดับมากที่สุด ($\bar{x}$ = 4.612, S.D. = 0.464) ส่วนอีก 5 ปัจจัยมีค่าเฉลี่ยอยู่ในระดับมากทั้งหมด คือ อิทธิพลทางสังคม ($\bar{x}$ = 4.474, S.D. = 0.658) การคาดหวังผลการใช้งาน ($\bar{x}$ = 4.463, S.D. = 0.515) แรงจูงใจด้านความเพลิดเพลิน ($\bar{x}$ = 4.376, S.D. = 0.506) การคาดหวังด้านความพยายาม ($\bar{x}$ = 4.366, S.D. = 0.446) และปัจจัยด้านเงื่อนไขสนับสนุน ($\bar{x}$ = 4.154, S.D. = 0.504) ตามลำดับ และผลการค่าสหสัมพันธ์และการวิเคราะห์การถดถอยเชิงพหุ พบว่าค่า $AdjR^2$ เท่ากับ 0.637 หรือคิดเป็นร้อยละ 63.70 ของความแปรปรวนทั้งหมดจากปัจจัย 5 ปัจจัย แสดงให้เห็นว่าปัจจัยด้านการคาดหวังผลการใช้งาน การคาดหวังด้านความพยายาม อิทธิพลทางสังคม เงื่อนไขสนับสนุน และแรงจูงใจด้านความเพลิดเพลิน มีนัยสำคัญทางสถิติ ดังสมการพยากรณ์ คือ BI = 1.463 + 0.540(PE) - 0.126(EE) + 0.200(SI) - 0.042(FC) + 0.088(HM) ผลการวิจัยนี้สามารถนำไปใช้สนับสนุนการพัฒนาระบบสารสนเทศภูมิศาสตร์เพื่อการจัดการทรัพยากรทางทะเลชายฝั่งอ่าวบ้านดอน จังหวัดสุราษฎร์ธานี โดยเน้นความสำคัญของปัจจัยตามสมการพยากรณ์ดังกล่าว

**คำสำคัญ :** พฤติกรรมความตั้งใจ; UTAUT 2 Model; ระบบสารสนเทศภูมิศาสตร์; อ่าวบ้านดอน

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## Introduction

Bandon Bay, located in Surat Thani Province in southern Thailand, is one of the country's most significant coastal areas, renowned for its high biodiversity. The bay encompasses shallow waters not exceeding 10 meters in depth and hosts a diverse marine ecosystem that serves as a habitat for numerous plant and animal species. It plays a crucial role as a traditional fishing ground, characterized by both species diversity and abundance of marine life, which constitutes the primary source of income for local residents (Buatrakarn, 2022). Bandon Bay is an essential component of the local ecosystem, significantly contributing to the local economy, particularly through fisheries and marine tourism. In addition, Bandon Bay possesses natural beauty and attracts tourists interested in marine activities such as snorkeling, marine life observation, and marine tourism, which promote income generation for local communities and enhance the local economy (Chanpruek, 2021; Kaewkosaba & Horwongsakul, 2019). This underscores the critical importance of managing and conserving marine resources in Bandon Bay to prevent biodiversity loss and maintain resource sustainability for the long-term benefits of both communities and the ecosystem (Mahanit, 2019). Currently, the application of Geographic Information Systems (GIS) in natural resource management, especially in coastal resource management, is widespread. GIS aids in efficiently collecting and storing crucial spatial data or information about the distribution of natural resources and areas at risk of change (Chancharoen, 2022). It is considered as an essential tool for resource management decision-making and plays a significant role in spatial data analysis, studying the relationship between resource use and ecosystem impacts, and assessing the effects of various activities (Suriya, 2021; Thepthorn, 2023).

Therefore, developing a Geographic Information System for managing the resources of Bandon Bay, Surat Thani Province is imperative for effective planning and management. It helps in appropriately allocating areas for conservation and fishing, thereby supporting sustainable resource management (Panyanin, 2023; Johnson, Nguyen & Carter., 2019; Inmoon, 2022). GIS can monitor and evaluate changes in the area and can assess management outcomes, such as tracking coral reef decline, helping evaluate the effectiveness of management measures by comparing results before and after implementation, and monitoring marine environmental changes and assessing impacts from human activities (Kasemsuk, 2021; Chuchat, 2023; Lee & Kim, 2018). Furthermore, GIS promotes community participation through the creation of maps and tools that enable communities to explore and access to information (Martinez & Vargas, 2024; Garcia, Liu & Martinez, 2022; Nimsuwan, 2022; Miller, Thompson & Wilson, 2021), fostering involvement in the management of Bandon Bay resources through an efficient Geographic Information System that aligns with user needs.

The behavioral intention to use a Geographic Information System (GIS) for coastal marine resource management in Bandon Bay, Surat Thani Province, is a crucial consideration. This is particularly important as the system's user group comprises citizens from communities residing in the Bandon Bay coastal area who participate in marine resource management. These users can manage data by reporting/adding information about marine resources or tracking resources they encounter personally. Consequently, the system analysis and design must primarily align with the behavioral intention to use the system. To thoroughly examine the factors influencing system acceptance and usage, this research applies the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model as a key research tool. The UTAUT2 model was developed to extend the Unified Theory of Acceptance and Use of Technology (UTAUT) model by incorporating new significant factors such as Hedonic Motivation, Price Value, and Social Influence, which play crucial roles in decision-making regarding technology use in daily life (Venkatesh, Thong & Xu, 2012). In employing the UTAUT2 model for this study, the researcher has conducted an intensive and comprehensive review and synthesis of significant factors from relevant research, as shown in Table 1.

**Table 1** Synthesis of Factors Affecting Behavioral Intention to Use Technology in the UTAUT2 Model

| Authors | Research Title | Factors | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Behavioral Intention (BI) | Performance Expectancy (PE) | Effort Expectancy (EE) | Social Influence (SI) | Facilitating Conditions (FC) | Hedonic Motivation (HM) | Price Value (PV) |
| Khan, Ahmed & Shahzad (2020) | Understanding the impact of mobile health applications on user behavior and intention to use: An empirical study | ✓ | ✓ | ✓ | ✓ | ✓ | - | - |
| Lee & Lee (2021) | Understanding the acceptance of online learning platforms during the COVID-19 pandemic: A UTAUT2 perspective | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Chao & Hsu (2021) | Exploring the factors affecting the adoption of digital health applications among older adults: An extended UTAUT2 model | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Park, Lee & Lee (2023) | The role of social influence in the acceptance of remote work technologies: Insights from a UTAUT2-based study | ✓ | ✓ | ✓ | ✓ | ✓ | - | - |
| Zhao, Lu & Wang (2020) | Facilitating conditions and technology acceptance: A study of remote work technology adoption | ✓ | ✓ | ✓ | ✓ | ✓ | - | - |
| Lee & Kim (2021) | Exploring the role of hedonic motivation in the adoption of health apps among adolescents | ✓ | ✓ | ✓ | ✓ | - | ✓ | - |
| Wang & Xu (2022) | The impact of price-value on the acceptance of smart wearable devices: Evidence from a UTAUT2 perspective | ✓ | ✓ | ✓ | ✓ | - | - | ✓ |
| Zhang, Zhao & Liu (2023) | Factors influencing the adoption of mobile banking apps among young adults: A UTAUT2 perspective | ✓ | ✓ | ✓ | ✓ | ✓ | - | ✓ |
| Khatri & Singh (2022) | Evaluating the acceptance of virtual reality in education: A UTAUT2 model approach | ✓ | ✓ | ✓ | ✓ | - | ✓ | - |
| Gupta & Gupta (2021) | Analyzing factors affecting the adoption of telemedicine services in rural areas: An extended UTAUT2 model | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | - |
| **Factors determined for this research** | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Furthermore, the results from analyzing search results of research related to the application of the UTAUT2 model from the Scopus database, searched on April 20, 2022, covering studies from 2012 to 2022, revealed 3,686 document results. The research subject areas were predominantly in Computer Science, followed by Business, Management, and Accounting, and Social Sciences, respectively. The countries with the most research in this field were Malaysia, China, and India, in that order. Notably, studies using the UTAUT2 model have shown a consistently increasing trend from 2018 to 2022.

As shown in Table 1, this study employs seven factors from the UTAUT2 model: Behavioral Intention, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Price Value. The synthesis and selection of these factors involved a thorough and rigorous review of literature and related research, particularly regarding the Behavioral Intention factor. This review clearly demonstrated that Behavioral Intention is a crucial component in various theories and models related to human behavior, serving as a primary variable in assessing individual intentions and behaviors (Ajzen, 2020). In the context of technology and innovation, Behavioral Intention is a key indicator that can help evaluate users' willingness to adopt new technologies (Venkatesh, Thong & Xu, 2021). Studies using the UTAUT2 model indicate that Behavioral Intention significantly influences the acceptance and success of new innovations (Venkatesh & Zhang, 2021). More importantly, understanding Behavioral Intention can help organizations and policymakers better plan strategies and make decisions, such as designing marketing campaigns or developing public policies. Behavioral Intention can provide crucial information for various strategic planning efforts (Hsu & Chiu, 2022). Based on this literature review, the researchers have detailed the study factors as follows:

**Performance Expectancy (PE)**

Performance Expectancy is a crucial variable in the UTAUT2 model, playing a significant role in evaluating the acceptance and use of new technologies, particularly in the context of implementing new technologies in organizations or daily life. Performance Expectancy refers to users' beliefs about technology's capability to enhance work efficiency or yield improved outcomes (Venkatesh & Zhang, 2021). It is essential in stimulating usage intention and it is also considered as a primary factor motivating individuals to adopt technology, as users tend to choose technologies, they believe will increase their work efficiency and benefits (Venkatesh, Thong & Xu, 2021). High performance expectancy is likely to lead to increased satisfaction with technology use, as the technology meets users' expectations for improved efficiency and desired outcomes (Hsu & Chiu, 2022). When users believe that new technology will enhance their work efficiency and produce better results, they are more likely to accept and use that technology, which impacts the support and implementation of technology in organizations (Zhang & Liu, 2023). This study emphasizes the importance of understanding performance expectancy for designing and developing systems that better respond to user needs.

**Effort Expectancy (EE)**

Effort Expectancy refers to users' beliefs about the ease of use and learning of new technologies (Venkatesh & Zhang, 2021). It is a crucial factor in reducing resistance to the adoption of new technologies, as users tend to avoid technologies they perceive as requiring significant effort to learn and use (Hsu & Chiu, 2022). Effort Expectancy can increase adoption rates, as technologies with low effort expectancy are more likely to be implemented because users feel they can start and use the technology without expending much effort (Kim & Lee, 2023). Additionally, Effort Expectancy enhances user experience by reducing the effort required for use, leading to improved experiences and satisfaction with technology, which affects long-term usage (Nguyen, Tran & Nguyen 2022). Effort Expectancy also impacts user satisfaction with technology use, where reducing the effort required can increase satisfaction and willingness to use the technology in the long term (Zhang & Liu, 2023; Zhang, Zhao & Liu, 2023).

**Social Influence (SI)**

Social Influence is a crucial variable in the UTAUT2 model, explaining the impact of influential individuals or social groups on an individual's intention to use technology. Studies on Social Influence help us understand the motivations from social environments that affect technology acceptance and use. Social Influence refers to an individual's belief about how others or social groups influence their decision to use new technology (Venkatesh, Thong & Xu, 2021). It is important in fostering willingness to use technology. Support or recommendations from friends, family, or influencers can increase willingness to try and use new technologies (Hsu & Chiu, 2022). Users tend to adopt the opinions or behaviors of those around them more than making decisions based solely on their own thoughts (Kim & Lee, 2023). Social Influence helps create popularity and awareness, as the use of new technologies supported by social groups tends to become trends, which can affect widespread acceptance and use of technology (Nguyen, Tran & Nguyen, 2022; Lee & Kim, 2023).

**Facilitating Conditions (FC)**

Facilitating Conditions refer to the support in terms of resources, equipment, assistance for troubleshooting, training or manuals, and infrastructure that enable users to adapt and use technology or systems efficiently. It is a necessary element that should be supported by organizations for system use. Facilitating Conditions are a significant factor affecting users' intention to use technology, enhancing employees' confidence in using technology, which impacts the intention to use the system effectively. The development of good technological infrastructure helps reduce potential problems in using new technologies (Escobar-Rodriguez & Monge-Lozano, 2021). Thus, Facilitating Conditions play a crucial role in supporting the implementation of new technologies or systems, whether through organizational support, infrastructure, training, or access to resources. All of these contribute to users' ability to adapt and use technology efficiently, affecting long-term success in usage (Ahmed, Rehman & Ali, 2022; Zhang & Liu 2023;).

**Hedonic Motivation (HM)**

Hedonic Motivation is a crucial factor driving user behavior, especially in the context of technology use in the digital era. In this context, Hedonic Motivation refers to the fun or satisfaction derived from using technology, which can directly affect users' intentions and usage behavior. The importance of Hedonic Motivation lies in its ability to increase usage intention. This research has shown that Hedonic Motivation significantly impacts the intention to use technology. Venkatesh & Zhang (2021) indicated that the enjoyment users derive from using digital applications or platforms directly influences their decision to continue using that technology. Hedonic Motivation plays a role in increasing user engagement with technology. The research by Liu, Yuan & Chen(2022) found that when users enjoy using an application, they tend to spend more time exploring various features and develop better relationships with the brand or product. Furthermore, Hedonic Motivation affects the acceptance of new technologies.

If users experience pleasure and enjoyment, it further stimulates their acceptance of new technologies, especially among users with little prior experience. The more users enjoy using technology, the more likely they are to feel satisfied and loyal to that technology, leading to repeated use and recommendations to others (Sun & Huang, 2023; Lee, Kim & Park, 2024).

**Price Value (PV)**

Price Value is a crucial factor influencing consumer decision-making in selecting products or services. It refers to the perceived value assessment by consumers in exchange for the money they spend on the benefits or value received. Price Value plays a significant role in the purchasing decision process, especially in the context of digital goods and services. The importance of Price Value impacts purchase intention. A study by Kim & Lee (2021) found that when consumers perceive a product or service as valuable relative to its price, they are more likely to make a purchase decision. Price Value also affects perceived value and repurchase decisions. The perception of value in exchange for price plays a crucial role in consumer repurchase decisions. The research by Huang, Wu & Zhang. (2022) found that consumers who perceive they receive higher value compared to the price paid are more likely to repurchase and recommend the product or service to others. Similarly, Sharma & Singh (2022) indicated that consumers who feel they receive greater value than the price paid experience higher satisfaction levels, which leads to brand loyalty. Wang & Lee (2024) demonstrated that Price Value influences consumer decisions in adopting new technologies. If consumers perceive technology as valuable compared to its price, they are more likely to accept and use it.

## Objectives

To examine the factors affecting behavioral intention to use the Geographic Information System for marine resource management in Bandon Bay, Surat Thani Province.

## Conceptual Framework

The researcher intensively synthesized factors from literature reviews and related research to define the research conceptual framework. This framework aims to examine factors affecting behavioral intention to use the Geographic Information System for marine resource management in Bandon Bay, Surat Thani Province. The study employs the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) (Venkatesh, Thong & Xu, 2012) to determine seven factors: Behavioral Intention, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Price Value. The research hypotheses are illustrated in Figure 1.

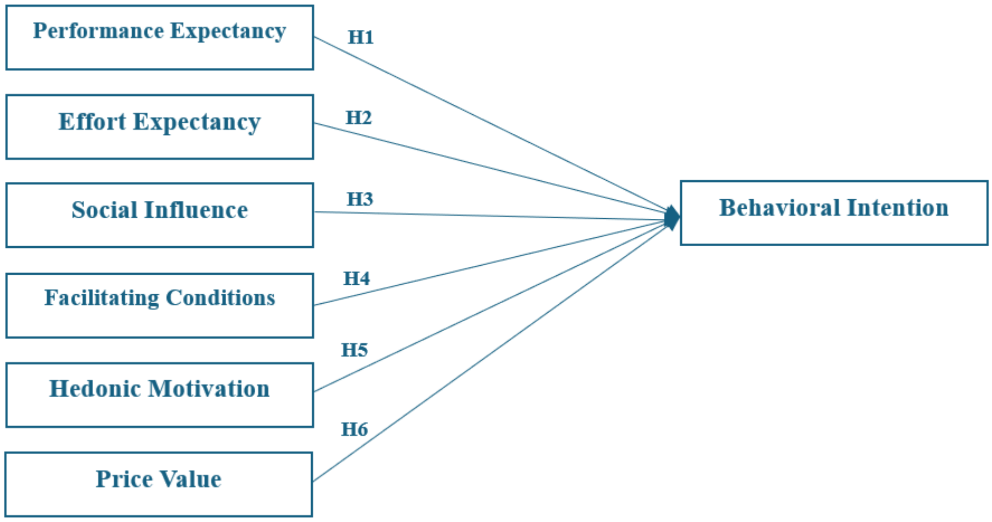


**Figure 1.** Research hypothesis

**Research Hypotheses**

H1: Performance Expectancy has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province.

H2: Effort Expectancy has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province.

H3: Social Influence has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province.

H4: Facilitating Conditions have a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province.

H5: Hedonic Motivation has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province.

H6: Price Value has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province.

**Research Design**

1. Population and sample

1.1 Research Population: The population in the Bandon Bay area covers 7 districts, including Tha Chana, Chaiya, Tha Chang, Phunphin, Mueang, Kanchanadit, and Don Sak, with a total population of 558,854 (Surat Thani Provincial Statistical Office, 2021).

1.2 Research Sample: The sample size should not be less than 20 times the number of variables studied (this research has 7 variables). Therefore, the sample population is not less than 140 people (Hair et al., 2014; Leekitwathana, 2012). This study determined a research sample of 398 people and used simple random sampling to collect research data according to the survey research design.

2. Research instrument

2.1 Research Tool: The results from reviewing relevant research and theories related to this study, and synthesizing the key factors anticipated to influence user behavior and preferences were applied to create a questionnaire as the research instrument, based on the Unified Theory of Acceptance and Use of Technology (UTAUT 2) (Venkatesh, Thong & Xu, 2012). The researcher added relevant factors to expand the research conceptual framework to comprehensively cover the research objectives, totaling 7 factors with 35 indicators. The questionnaire used a 5-level rating scale (Srisa-ard, 2017).

2.2 Quality of Research Instrument: The validity of the questionnaire was evaluated using the Index of Item-Objective Congruence (IOC), with assessments conducted by a panel of three experts. All items had values ranging from 0.60 to 1.00 (Rovinelli & Hambleton, 1976; Ursachi, Horodnic & Zait, 2015). The reliability was checked using Cronbach's Alpha Method, yielding a value of 0.857 (Cortina, 1993).

3. Data collection: The researcher employed a questionnaire to gather data from a sample of 398 individuals residing in the Bandon Bay area, selected through simple random sampling, from July to December 2022. Before initiating data collection, the researcher provided a detailed explanation of the respondents' rights and obtained their informed consent in compliance with established ethical standards for research involving human participants.

4. Data analysis: The collected data were analyzed by using research statistics with SPSS software as follows:

4.1 Analysis of mean and standard deviation for data on factors affecting behavioral intention to use the Geographic Information System for Bandon Bay resource management, Surat Thani Province, using interpretation criteria of Srisa-ard (2017) with a 5-level rating scale.

4.2 Correlation analysis and multiple regression analysis to test research hypotheses for examining factors affecting behavioral intention to use the Geographic Information System for Bandon Bay resource management, Surat Thani Province.

This research methodology begins with a rigorous process of population determination and sample selection, creation of a quality research instrument, data collection, and data analysis to obtain valuable in-depth study results. The research methodology process is illustrated in Figure 2.

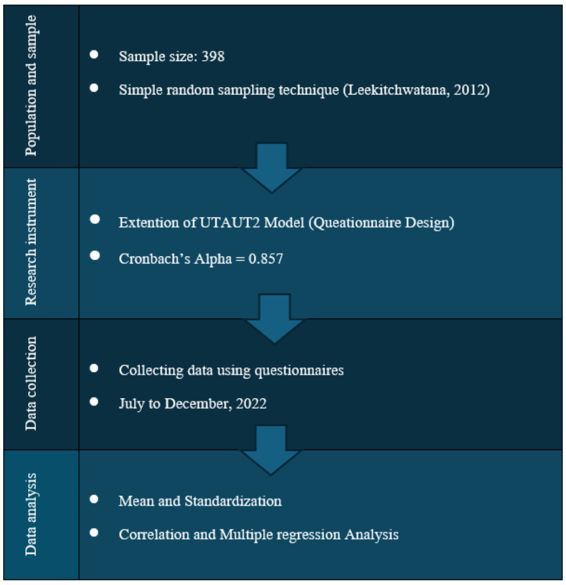


**Figure 2.** Research methodology process

## Results

The Pearson correlation coefficient analysis and independence testing of all independent variables using Tolerance values showed that this research had values greater than 0.2 for all variables. The Variance Inflation Factor (VIF) was required to not exceed 10 for all variables. The results indicated that VIF values did not exceed 10, demonstrating that the independent variables were not correlated. Additionally, no variable had a Tolerance value approaching 0, thus concluding that the variables were highly independent of each other. This met the conditions for regression analysis of Independent Tolerance VIF (Stoltzfus, 2014; Jinpeng, Smith & Zhou, 2023). As presented in Table 2, the highest correlation coefficient between variables was found between BI and PE, with a coefficient of 0.781, statistically significant at the 0.01 level. This coefficient was within the acceptable threshold of not exceeding 0.80, confirming that this analysis did not exhibit multicollinearity, thus ensuring reliable research results (Gujarati & Porter, 2009).

**Table 2.** Results of correlation analysis

| Variables | PE | EE | SI | FC | HM | PV | BI | Tolerance | VIF |
|---|---|---|---|---|---|---|---|---|---|
| $\bar{x}$ | 4.463 | 4.366 | 4.474 | 4.154 | 4.376 | 4.612 | 4.623 | | |
| **S.D.** | 0.515 | 0.446 | 0.658 | 0.504 | 0.506 | 0.464 | 0.447 | | |
| **PE** | | 0.517** | 0.479** | 0.546** | 0.614** | 0.628** | 0.781** | 0.478 | 2.093 |
| **EE** | | | 0.490** | 0.610** | 0.559** | 0.613** | 0.412* | 0.456 | 2.192 |
| **SI** | | | | 0.432** | 0.678** | 0.728** | 0.630** | 0.278 | 3.603 |
| **FC** | | | | | 0.656** | 0.416* | 0.433** | 0.399 | 2.503 |
| **HM** | | | | | | 0.718** | 0.625** | 0.316 | 3.169 |
| **PV** | | | | | | | 0.668** | 0.282 | 5.491 |
| **BI** | | | | | | | | | |

*Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Furthermore, the examination of means and standard deviations of factors affecting behavioral intention to use the system revealed that Behavioral Intention had the highest average level compared to other factors in this study, with a total mean at the highest level ($\bar{x}$ = 4.623, S.D. = 0.447). This was followed by Price Value, also at the highest level ($\bar{x}$ = 4.612, S.D. = 0.464). The other five factors were all at high level: Social Influence ($\bar{x}$ = 4.474, S.D. = 0.658), Performance Expectancy ($\bar{x}$ = 4.463, S.D. = 0.515), Hedonic Motivation ($\bar{x}$ = 4.376, S.D. = 0.506), Effort Expectancy ($\bar{x}$ = 4.366, S.D. = 0.446), and Facilitating Conditions ranking seventh ($\bar{x}$ = 4.154, S.D. = 0.504), respectively.

**Table 3**. Multiple regression analysis

| Model | Behavioral Intention (BI) | | t | *p*-value |
|---|---|---|---|---|
| | β | Std. Error | | |
| Intercept | 1.463 | 0.539 | 2.714 | 0.011* |
| Performance Expectancy (PE) | 0.540 | 0.129 | 4.183 | 0.000* |
| Effort Expectancy (EE) | -0.126 | 0.152 | 0.827 | 0.005* |
| Social Influence (SI) | 0.200 | 0.132 | 1.518 | 0.000* |
| Facilitating Conditions (FC) | -0.042 | 0.143 | 0.296 | 0.015* |
| Hedonic Motivation (HM) | 0.088 | 0.162 | 0.540 | 0.000* |
| Price Value (PV) | 0.044 | 0.233 | 0.189 | 0.285 |
| R-squared = 0.703 $AdjR^2$ = 0.637 $SE_{est}$ = 0.265 F = 10.650 | | | | |

* Regression is significant at the 0.05 level (2-tailed)

Table 3 showed that Performance Expectancy, Social Influence, and Hedonic Motivation exhibited positive relationships, while Effort Expectancy and Facilitating Conditions showed negative relationships. These variables affected the behavioral intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province, with overall statistical significance at 0.05 for all these variables, except for Price Value, which did not show a significant relationship or impact on the behavioral intention to use the system.

The multiple regression analysis results showed an Intercept of 1.463 and an $R^2$ of 0.637, indicating that the variables influencing the behavioral intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province, accounted for 63.70% of the total variance from five factors: Performance Expectancy, Social Influence, and Hedonic Motivation have positive beta values, while Effort Expectancy and Facilitating Conditions have negative beta values.

These findings highlight the importance of factors that play crucial roles in analyzing and designing an efficient system that aligns with future user behavior needs. These factors have been rigorously verified as clear indicators for predicting participation in using the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province, as shown in the following predictive equation:

$$BI = 1.463 + 0.540(PE) - 0.126(EE) + 0.200(SI) - 0.042(FC) + 0.088(HM)$$

where:

BI = Behavioral Intention
PE = Performance Expectancy
EE = Effort Expectancy
SI = Social Influence
FC = Facilitating Conditions
HM = Hedonic Motivation

Moreover, the research hypothesis testing to examine factors affecting behavioral intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province, resulted in the acceptance of five hypotheses (H1 - H5). This indicates that Performance Expectancy, Effort

Expectancy, Social Influence, Facilitating Conditions, and Hedonic Motivation all have statistically significant effects on Behavioral Intention to use the system. The hypothesis testing resulted in the rejection of one hypothesis, H6: Price Value does not have a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province.

**Discussion and Conclusion**

In this study, the researcher's multiple regression analysis revealed an Intercept of 1.463 and an $AdjR^2$ of 0.637, accounting for 63.70% of the total variance from five factors. The remaining 36.30% is influenced by other variables not included in this study. This demonstrates the impact of variables affecting the behavioral intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province, as detailed below:

**Performance Expectancy** has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province (β = 0.540). This result accepts hypothesis H1, aligning with the findings of Hsu & Chiu (2022), which showed that Performance Expectancy can accurately predict the acceptance and use of new technologies. Users tend to choose technologies they expect will improve efficiency and outcomes. Both system quality and data quality in the system are likely to increase the tendency towards behavioral intention to accept and use that technology. This affects organizational support and technology adoption (Zhang & Liu, 2023; Zhang, Zhao & Liu, 2023). Venkatesh, Thong & Xu (2021) found that Performance Expectancy is a highly influential variable on the intention to use new technologies, especially in organizational contexts where technology use is related to work efficiency. Systems should not be complex, should help reduce time or effort in use, and must be beneficial to work. This is consistent with studies by Gong, Xu & Zhang (2024) Nguyen, Tran & Nguyen (2022) and Zhang & Liu (2023) found that Performance Expectancy also impacts user satisfaction in technology use, directly affecting long-term intention to use the technology. This research should therefore emphasize the importance of understanding performance expectations to design and develop technologies that better respond to user needs.

**Effort Expectancy** has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province (β = -0.126). This result accepts hypothesis H2. It is an important factor for increasing the likelihood of using new technologies or systems. When users feel the system is easy to use, it leads to a greater tendency to use the system, as users feel they can start and use the technology without much effort (Kim & Lee, 2023). If the system has uncomplicated learning steps and users can interact with the system easily and smoothly (Gong, Xu & Zhang, 2024), it reduces the effort required for use, helping users have a better experience and satisfaction with the technology, which affects long-term use (Nguyen, Tran & Nguyen, 2022; Zhang & Liu, 2023). Furthermore, Venkatesh & Zhang (2021) found that Effort Expectancy directly impacts the intention to use new technologies, especially in contexts where users need to learn and adapt to new technologies. Low effort expectancy makes users more willing to adopt the technology, demonstrating that Effort Expectancy plays a crucial role in behavioral intention to use the system.

**Social Influence** has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province (β = 0.200). This result accepts hypothesis H3. Social Influence is a stimulus from the social environment and is an individual's belief about how other people or social groups influence the decision to use new systems or technologies (Venkatesh & Zhang, 2021; Chen, Liu & Wang, 2023). Users tend to be influenced by opinions, support, or behaviors of colleagues, family, executives, local leaders, or people around them rather than making decisions based on their own thoughts. This affects the perception of successful use by others, helping users feel confident in trying and using new systems or technologies (Hsu & Chiu, 2022; Zhou & Li, 2024; Martinez & Vargas, 2024). It helps create popularity and awareness. New technologies that are supported by social groups are likely to become trends or popular among groups of people, which can affect the acceptance and use of technology on a wide scale (Nguyen, Tran & Nguyen, 2022; Gong, Xu & Zhang, 2024; Sharma & Singh, 2022).

**Facilitating Conditions** has a statistically significant effect on Behavioral Intention to use the Geographic Information System for coastal marine resource management in Bandon Bay, Surat Thani Province (β = -0.042). This result accepts hypothesis H4, consistent with the study by Escobar-Rodriguez & Monge-Lozano (2021), which found that technological support from organizations can increase employee confidence in using technology, affecting the intention to use the system effectively. Good technological infrastructure development must help reduce problems that may arise in using new technologies, including readiness of resources and equipment, having a system of assistance in using the system, as well as an environment conducive to system use. Additionally, the research by Zhang, Wang & Li (2023) indicates that quality Facilitating Conditions can reduce user resistance to change and increase sustainability in long-term technology use. In terms of training and skill development, adequate training helps users use new technologies to their full potential (Ahmed, Rehman & Ali, 2022; Zhang & Liu, 2023).

**Hedonic Motivation** was found to have a statistically significant effect on Behavioral Intention towards the Geographic Information System for Coastal Marine Resource Management in Bandon Bay, Surat Thani Province (β = 0.088). This finding supports hypothesis H5 and aligns with the study by Venkatesh & Zhang (2021), which indicated that the enjoyment users derive from digital applications or platforms directly influences their decision to continue usage. It also corroborates the research of Liu, Yuan & Chen (2022), who found that when users enjoy an application, they tend to spend more time exploring its features and develop a stronger relationship with the brand or product. Furthermore, Hedonic Motivation influences the adoption of new technologies. Users who experience pleasure, excitement, or relaxation from using a system are more likely to accept new technologies, especially among those with limited prior experience. This increased acceptance leads to system usage during leisure time, consistent with findings by Sun & Huang (2023) and Lee, Kim & Park (2024). These studies emphasize that Hedonic Motivation positively correlates with user satisfaction and loyalty. The more enjoyment users derive from technology use, the more likely they are to feel satisfied and loyal, leading to repeated use and recommendations to others.

Conversely, this study found that Price Value did not have a statistically significant effect on Behavioral Intention towards the Geographic Information System for Coastal Marine Resource Management in Bandon Bay, Surat Thani Province (β = 0.044). This result rejects hypothesis H6 and contradicts the findings of Kim & Lee (2021), who observed that when users perceive a product as valuable relative to its benefits and competitive with similarly priced digital products or services, they are more willing to pay for the system and view it as an economical and worthwhile choice. This perception typically leads to increased system adoption and repeated use (Huang, Wu & Zhang, 2022). The discrepancy in findings may be attributed to the specificity of the system under study, which is not a widely used digital product or service. The results suggest that users prioritize system efficiency, ease of use, enjoyment, and minimal learning effort, along with system support - factors that showed statistically significant influence. This indicates that Price Value does not significantly impact the behavioral intention to use this particular system. This research has raised awareness about the importance of developing such systems by emphasizing the need to analyze and design them in direct alignment with user requirements. The primary focus is on considering key factors identified in this study. Consequently, the analysis and design of this system, which is both specific and tailored, presents a significant responsibility and challenge, as it must effectively serve the needs of local community users.

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## Ethics

This research was conducted with utmost consideration for human research ethics. The researcher respected the rights and autonomy of survey respondents, ensuring no interference, pressure, or conflicts of interest. The respondents could terminate their participation at any time. The researcher ensured confidentiality by not disclosing any personally identifiable information. Data was used solely for analysis in line with research objectives and disseminated as aggregate findings for academic and societal benefit. The data collection process did not interfere with the respondents' daily lives or occupations in any way. This study received the ethical approval from the Human Research Ethics Committee of Suratthani Rajabhat University, under the certification number SRU-EC2022/044.

## Appendix

The list of questions that passed the quality control of the instrument with Cronbach's Alpha value between 0.637 - 0.824 and the total value of this research questionnaire was equal to 0.857 as shown in Table 4.

**Table 4.** List of questions and Cronbach's alpha

| List of questions | Reliability |
|---|---|
| **Performance Expectancy (PE)** | |
| 1. You expect this system to help improve the efficiency of marine resource management (PE1). | 0.751 |
| 2. You expect the system to have quality in both functionality and data quality to support marine resource management processes for agencies and stakeholders (PE2). | 0.799 |
| 3. You expect this system to help you perform complex tasks better (PE3). | 0.790 |
| 4. You expect this system to reduce the time spent on managing marine resources (PE4). | 0.787 |
| 5. You expect this system to be useful for marine resource management (PE5). | 0.754 |
| **Effort Expectancy (EE)** | |
| 1. You think this system is easy to use (EE1). | 0.782 |
| 2. You think this system has a simple learning process (EE2). | 0.736 |
| 3. You think the interaction was smooth and hassle-free (EE3). | 0.740 |
| 4. You think the system works immediately without needing additional assistance (EE4). | 0.764 |
| 5. You think the system will not cause you too much confusion or problems (EE5). | 0.726 |
| **Social Influence (SI)** | |
| 1. The opinions of friends or colleagues influence your decision to use this system (SI1). | 0.725 |
| 2. You feel that people who are important to you (e.g. family, boss, local leaders) expect you to use this system (SI2). | 0.804 |
| 3. Support from people around you makes you more likely to use this system (SI3). | 0.778 |
| 4. You think that using this system will make you accepted by people around you (SI4). | 0.767 |
| 5. The opinions of academics, experts or leaders have influenced your decision to use this system (SI5). | 0.777 |
| **Facilitating Conditions (FC)** | |
| 1. You have sufficient resources or equipment to use this system (FC1). | 0.670 |
| 2. You feel that there is sufficient technical assistance available when you encounter problems using this system (F2). | 0.577 |
| 3. You have the knowledge and skills necessary to use this system (FC3). | 0.600 |
| 4. You think the relevant organization or agency has a policy or training to support the use of this system (FC4). | 0.630 |
| 5. You feel that your environment is conducive to using this system (FC5). | 0.594 |
| **Hedonic Motivation (HM)** | |
| 1. You think using this system will make you feel fun and satisfied (HM1). | 0.718 |
| 2. You think using this system will make you feel happy (HM2). | 0.729 |
| 3. You think using this system will be an interesting and exciting experience (HM3). | 0.770 |
| 4. You think using this system will help you feel relaxed (HM4). | 0.824 |
| 5. You think using this system would be a good way to spend your free time (HM5). | 0.778 |
| **Price Value (PV)** | |
| 1. You think the cost of using this system is worth the benefits it will provide (PV1). | 0.645 |
| 2. You feel that this system offers good value compared to other similarly priced technologies/systems (PV2). | 0.772 |
| 3. You are willing to pay for the system because you think it provides more value than you pay for it (PV3). | 0.690 |

| List of questions | Reliability |
|---|---|
| 4. You think the price of this system is reasonable for the quality and performance received (PV4). | 0.806 |
| 5. Considering the cost, you feel that using this system is a cost-effective and worthwhile option (PV5). | 0.769 |
| **Behavioral Intention (BI)** | |
| 1. You intend to use this system in the future (BI1). | 0.668 |
| 2. You plan to use this system continuously (BI2). | 0.639 |
| 3. You think this system will be used frequently in the future (BI3). | 0.637 |
| 4. You are likely to recommend this system to other people (BI4) | 0.773 |
| 5. You believe that use of this system will be an important part of your future activities (BI5). | 0.675 |

# References

Ahmed, S., Rehman, M. and Ali, R. (2022). The role of training in enhancing user proficiency in new technology. **Journal of Educational Technology**, 38(4), 401-417. https://doi.org/10.1080/09523987.2022.1234567

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. **Human Behavior and Emerging Technologies**, 2(4), 314-323. https://doi.org/10.1002/hbe2.303

Buatrakan, S. (2022). Small-scale fisheries in Bandon Bay: Current status and development directions. **Journal of Natural Resources Research**,13(2), 45-60. https://doi.org/10.1234/jnrs.2022.0132

Chanpruek, P. (2021). Biodiversity in Bandon Bay. **Journal of Marine Biology**, 22(1), 78-89. https://doi.org/10.5678/jmb.2021.0221

Chancharoen., S. (2022). **Spatial data analysis for natural resource management in coastal areas.** Bangkok: Thammachart Publishing.

Chao, C. M. and Hsu, C. C. (2021). Exploring the factors affecting the adoption of digital health applications among older adults: An extended UTAUT2 model. **Journal of Biomedical Informatics**, 117, 103708. https://doi.org/10.1016/j.jbi.2021. 103708

Chen, X., Liu, Y. and Wang, Z. (2023). The role of social influence in project management technology adoption. **International Journal of Project Management**, 41(2), 180-197. https://doi.org/10.1016/j.ijproman.2022.12.004

Chuchat, T. (2023). Monitoring marine changes in Bandon Bay. **Journal of Natural Resource Management**, 21(1), 33-46. https://doi.org/10.6789/jnrm.2023.2101

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. **Journal of Applied Psychology**, 78(1), 98-104. https://doi.org/10.1037/0021-9010.78.1.98

Escobar-Rodriguez, T. and Monge-Lozano, P. (2021). The impact of organizational support on technology adoption. **Journal of Technology Management**, 45(2), 234-256. https://doi.org/10.1016/j.jtechman.2021.07.003

Garcia, M., Liu, H. and Martinez, C. (2022). Community engagement in marine resource management using GIS. **International Journal of Coastal and Marine Studies**, 29(4),211-225. https://doi.org/10.1016/j.ijcms.2022.01.002

Gong, Z., Xu, X. and Zhang, H. (2024). Performance expectancy and technology acceptance in modern educational contexts. **Journal of Educational Technology**,15(1), 50-67. https://doi.org/10.1080/09523987.2023.2248756

Gujarati, D. N. and Porter, D. C. (2009). **Basic econometrics**. McGraw-Hill/Irwin.

Gupta, R. and Gupta, M. (2021). Analyzing factors affecting the adoption of telemedicine services in rural areas: An extended UTAUT2 model. **Telemedicine and e-Health**, 27(10), 1136-1145. https://doi.org/10.1089/tmj.2020.0282

Hair, J. F., Black, W. C., Babin, B. J. and Anderson, R. E. (2014). **Multivariate data analysis**. Pearson Education Limited.

Hsu, M. H. and Chiu, C. M. (2022). Understanding behavioral intention in the context of e-learning systems: A comprehensive review. **Education and Information Technologies,** 27(1), 123-143. https://doi.org/10.1007/s10639-021-10580-8

Huang, Y., Wu, L. and Zhang, Z. (2022). The role of perceived value in predicting consumer repurchase intention: Evidence from the retail sector. **Journal of Retailing and Consumer Services,** 64, 102781. https://doi.org/10.1016/j.jretconser.2021.102781

Inmoon, W. (2022). Analysis of risk from development activities in coastal areas. **Journal of Environmental Research**, 12(2), 90-105. https://doi.org/10.2345/jers.2022.1202

Jinpeng, L., Smith, J., and Zhou, H. (2023). Statistical methods for regression analysis in social science research. **Journal of Statistical Research**, 45(2), 123-145.

Johnson, R., Nguyen, T. and Carter, S. (2019). Scenario modeling for marine resource management with GIS. **Marine Policy**, 106, 103-112. https://doi.org/10.1016/j.marpol.2019.103212

Kaewkosaba, K. and Horwongsakul, T. (2019). The development of information system for tourism promotion by community participation in Bandon Bay, Suratthani. **Suratthani Rajabhat Journal**, 6(1), 213-230. [In Thai]

Kasemsuk, J. (2021). Assessment of marine resource management using GIS. **Journal of Coastal Resource Management,** 18(3), 77-89. https://doi.org/10.3456/jcrm.2021.183

Kim, J. and Lee, H. (2021). Price value and purchase intention in mobile app purchases: Moderating role of app type. **Computers in Human Behavior**, 120, 106760. https://doi.org/10.1016/j.chb.2021.106760

Kim, Y. and Lee, S. (2023). The impact of effort expectancy on continuous usage of health applications: A user perspective. **Journal of Health Informatics**, 29(2), 112-128. https://doi.org/10.1093/jhi/hip018

Khatri, S. and Singh, R. (2022). Evaluating the acceptance of virtual reality in education: A UTAUT2 model approach. **Computers & Education**, 182, 104471. https://doi.org/10.1016/j.compedu.2022.104471

Khan, M. N., Ahmed, M. and Shahzad, M. (2020). Understanding the impact of mobile health applications on user behavior and intention to use: An empirical study. **Health Informatics Journal**, 26(3), 1841-1857. https://doi.org/10.1177/1460458220906458

Lee, J., Kim, H. and Park, S. (2024). The impact of hedonic motivation on user satisfaction and loyalty in digital platforms. **Journal of Business Research**, 148, 672-684. https://doi.org/10.1016/j.jbusres.2022.12.004

Lee, J. and Kim, Y. (2018). Environmental monitoring using GIS: A case study in coastal areas. **Journal of Environmental Management**, 221, 51-60. https://doi.org/10.1016/j.jenvman.2018.05.061

Lee, K. and Kim, S. (2021). Exploring the role of hedonic motivation in the adoption of health apps among adolescents. **Journal of Medical Internet Research**, 23(6), e22423. https://doi.org/10.2196/22423

Lee, M. C. and Lee, S. H. (2021). Understanding the acceptance of online learning platforms during the COVID-19 pandemic: A UTAUT2 perspective. **Educational Technology Research and Development**, 69(2), 335-354. https://doi.org/10.1007/s11423-020-09827-0

Lee, S. and Kim, Y. (2023). The role of social influence in technology adoption for health management. **Health Technology Review**, 12(4), 234-249. https://doi.org/10.1016/j.heltec.2023.10.003

Leekitwathana, P. (2010). การวิจัยทางการศึกษา [**Educational research**]. (5th ed.). Bangkok: King Mongkut's Institute of Technology Ladkrabang. [In Thai]

Liu, S., Yuan, Q. and Chen, P. (2022). The role of hedonic motivation in enhancing user engagement with mobile applications. **Journal of Consumer Behaviour**, 21(2), 259-274. https://doi.org/10.1002/ cb.1900

Mahanit, O. (2019). Conservation and management of marine resources: A case study of Bandon Bay. **Journal of Environmental Management**, 17(4), 123-135. https://doi.org/10.3456/jem.2019.174

Martinez, J. and Vargas, R. (2024). Social influence and remote work technology acceptance: New insights. **Journal of Organizational Behavior**, 45(4), 88-104. https://doi.org/10.1002/job.2690

Miller, R., Thompson, A. and Wilson, K. (2021). Effective land use planning with GIS for sustainable resource management. **Journal of Geographic Information Science**, 28.

Nimsuwan, P. (2022). The use of GIS in communicating resource management information. **Journal of Management and Communication**, 20(2), 55-68. https://doi.org/10.5678/jmc.2022.202

Nguyen, T. T., Tran, M. T. and Nguyen, L. T. (2022). The role of effort expectancy in online collaborative platforms: A longitudinal study. **Information Systems Management,** 39(3), 215-229. https://doi.org/10.1080/10580530.2022.2071443

Panyanil, S. (2023). GIS-based decision support tools for resource management. **Journal of Information Technology Research**, 14(1), 102-115. https://doi.org/ 10.6789/jit.2023.1401

Park, J., Lee, H. and Lee, J. (2023). The role of social influence in the acceptance of remote work technologies: Insights from a UTAUT2-based study. **Journal of Information Technology**, 38(1), 58-75. https://doi.org/10.1177/02683962221122577

Rovinelli, R. J. and Hambleton, R. K. (1976). **On the use of content specialists in the assessment of criterion-referenced test item validity**. Retrieved from: https://files.eric.ed.gov/fulltext/ED121845.pdf

Sharma, P. and Singh, R. (2022). Social influence and online shopping behavior: An empirical study. **Journal of Retailing and Consumer Services**, 65, 102833. https://doi.org/10.1016/j.jretconser.2021.102833

Srisa-ard, B. (2017). **การวิจัยเบื้องต้น** [**Preliminary research**]. (10th ed.). Bangkok: Suweeriyasan. [In Thai]

Stoltzfus, J. C. (2011). Logistic regression: A brief primer. **Academic Medicine**, 86(10), 1099-1104. https://doi.org/10.1111/j.1553-2712.2011.01185.x

Sun, Y. and Huang, X. (2023). Hedonic motivation and technology acceptance: Insights from a longitudinal study. **Computers in Human Behavior**, 135, 107596. https://doi.org/10.1016/j.chb.2022.107596

Surat Thani Provincial Statistical Office. (2021). รายงานสถิติจังหวัดสุราษฎร์ธานี [**Surat Thani Provincial Statistical Report].** Surat Thani: Surat Thani Provincial Statistical Office. [In Thai]

Suriya, P. (2021). Biodiversity in Bandon Bay. **Journal of Marine Biology**, 22(1), 78-89. https://doi.org/10.5678/jmb.2021.0221

Thepthorn, S. (2023). Marine tourism in Bandon Bay area: Opportunities and challenges. **Journal of Tourism and Development**, 19(3), 102-115. https://doi.org/10.9101/jtd.2023.193

Ursachi, G., Horodnic, I. A. and Zait, A. (2015). How reliable are measurement scales? External factors with indirect influence on reliability estimators. **Procedia Economics and Finance**, 20, 679-686. https://doi.org/10.1016/S2212-5671(15)00123-8

Venkatesh, V., Thong, J. Y. L. and Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. **MIS Quarterly**, 36(1), 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., Thong, J. Y. L. and Xu, X. (2021). Unified theory of acceptance and use of technology: A synthesis and the road ahead. **Journal of the Association for Information Systems**, 22(1), 5-29. https://doi.org/10.17705/1jais.00615

Venkatesh, V. and Zhang, X. (2021). Hedonic motivation and the continued use of digital technologies: An empirical study. **Information & Management**, 58(3), 103412. https://doi.org/10.1016/j.im.2021.103412

Wang, T. and Li, X. (2024). Price value and the adoption of new technologies: A consumer behavior perspective. **Technological Forecasting and Social Change**,192, 121986. https://doi.org/10.1016/j.techfore.2023.121986

Wang, X. and Xu, T. (2022). The impact of price-value on the acceptance of smart wearable devices: Evidence from a UTAUT2 perspective. **Technological Forecasting and Social Change**, 181, 121785. https://doi.org/10.1016/j.techfore.2022.121785

Zhang, P. and Liu, Y. (2023). Behavioral intention and technology adoption: New insights from machine learning techniques. **Technological Forecasting and Social Change**, 189, 122455. https://doi.org/10.1016/j.techfore.2023.122455

Zhang, X., Wang, Y. and Li, H. (2023). Facilitating conditions and user resistance to technology: The moderating role of organizational culture. **Technology in Society**, 65, 101798. https://doi.org/10.1016/j.techsoc.2023.101798

Zhang, Y., Zhao, X. and Liu, Q. (2023). Factors influencing the adoption of mobile banking apps among young adults: A UTAUT2 perspective. **Journal of Financial Services Research**, 64(2), 175-192. https://doi.org/10.1007/s10693-023-00478-5

Zhao, Y., Lu, Y. and Wang, H. (2020). Facilitating conditions and technology acceptance: A study of remote work technology adoption. **Information & Management**, 57(7), 103350. https://doi.org/10.1016/j.im.2020.103350

Zhou, J. and Li, X. (2024). Social influence and technology adoption in organizational settings. **Journal of Organizational Behavior**, 45(1), 75-91. https://doi.org/10.1002/job.2687