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OPTIMIZING TOURISM SERVICE INTELLIGENT RECOMMENDATION SYSTEM BY MULTI-AGENT REINFORCEMENT LEARNING FOR SMART CITIES DESTINATION

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Abstract: *The tourism sector is in a state of continual evolution, marked by a growing demand from travellers for customized and individualized experiences within smart city destinations. In response to this evolving landscape, this research introduces an innovative approach to intelligent recommendation systems for tourism services, utilizing Multi-Agent Reinforcement Learning (MARL). The proposed methodology employs a centralized critic and decentralized actor architecture to capture intricate interactions among agents, thereby generating recommendations of superior quality. Performance evaluation conducted on a real-world dataset demonstrates the method's superiority over existing approaches in terms of recommendation accuracy and diversity. Furthermore, this paper introduces a tourism service recommendation system based on MARL and assesses its efficacy using five distinct algorithms: Real, Random, DQN, DDPG, and MADDPG. Results indicate that the MADDPG algorithm surpasses other algorithms in providing reliable, efficient, and cost-effective services to tourists. MADDPG's capacity to learn and adapt to shifting user preferences and behaviours, facilitated by a centralized critic and decentralized actors learning from agent-environment interactions, enables it to adeptly navigate complex and dynamic environments. Moreover, the research delves into the implications of these findings for the tourism industry, drawing insights from feedback obtained from 400 respondents. The results reveal a high degree of user satisfaction with the optimized tourism service recommendation system in smart city destinations, consequently fostering a strong intention among users to revisit. This study represents a notable advancement in augmenting the tourism experience through sophisticated recommendation systems tailored for smart city destinations.*

Keywords*: Machine Learning, Multi-Agent Reinforcement Learning, Recommended Systems, Service Recommendation Systems, Smart Cities, Tourism Servies.*

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1. Introduction

In the era of digitization, the advent of artificial intelligence (AI) has emerged as a transformative influence across diverse industries, notably within the tourism sector. Its potential to fundamentally alter the modes of delivery, marketing, and management of tourism services underscores its pivotal role in reshaping industry dynamics (Sarkar et al., 2023; Suanpang et al., 2022b). Leveraging AI in the realm of tourism engenders diverse advantages, particularly in the realms of personalization and customer experience enhancement. Concurrently, given the escalating prevalence of travel, there exists a heightened need for tailored and seamless tourism experiences. In recent years, AI has arisen as a potent instrument, contributing significantly to the augmentation of various facets within the tourism industry, spanning marketing strategies, customer service optimization, destination management, and global sustainability initiatives (Suanpang et al., 2022b).

In this context, a Tourism Services Intelligent Recommended System (TSIR) employs artificial intelligence, machine learning algorithms, and multi-agent systems to analyse extensive datasets encompassing user preferences, behavioural patterns, historical data, and contextual factors. The objective is to derive personalized recommendations informed by a comprehensive understanding of the aforementioned variables (Suanpang et al., 2022b; Zhang et al., 2022). The TSIR has the potential to play a role in advancing sustainable tourism practices by integrating criteria that advocate for environmentally conscious selections. This may entail recommending eco-friendly accommodations or activities designed to mitigate ecological impact (Suanpang et al., 2022b; Zhang et al., 2022). This procedural undertaking holds paramount significance in enhancing the holistic travel experience for tourists and streamlining the planning process. Through the furnishing of pertinent and personalized information to tourists, providers of tourism services can enhance customer satisfaction and engender loyalty, consequently augmenting revenue streams and securing a competitive edge vis-à-vis their counterparts (Joseph & Santiago, 2021; Suanpang et al., 2022b; Zhou et al., 2020).

Yet, prevalent tourism service recommendations frequently encounter constraints pertaining to restricted personalization, scalability, and adaptability. Furthermore, the dynamic and uncertain characteristics of the tourism environment pose challenges in devising an efficacious recommendation system (Suanpang et al., 2022b). This paper suggests a novel solution to tackle these issues—a tourism service recommendation approach using MARL. MARL integrates reinforcement learning and multi-agent systems, fostering collaborative learning among agents to optimize rewards in a competitive and cooperative environment (Yeo et al., 2020). In the process of planning tourism endeavours, individuals necessitate substantial and precise information to underpin their decision-making regarding destination selection. This is pivotal in averting unsatisfactory tourism experiences, mitigating the potential for escalated costs and inefficiencies (Suanpang et al., 2022b; Zhang et al., 2022). In order to address these challenges and augment the holistic travel experience, it becomes imperative to furnish recommendations for tourist services. Enhancing the effectiveness of the journey encompasses cost reduction (CP), diminution of wait times (CWT), and optimization of the Service Failure Rate (SFR).

The TRS issue diverges from conventional recommendation tasks when approached from two perspectives (Suanpang et al., 2022a). Primarily, a scarcity of service providers in a preferred locale may give rise to potential resource competition among travellers. Additionally, service recommendations may transiently impede the availability of service providers for a limited duration, contingent upon the service's availability and duration (Zhang et al., 2022). Historically, attempts to recommend tourism services using greedy strategies have overlooked the persistent challenge of spatiotemporally imbalanced service demands and constrained service capacity. This oversight yields suboptimal global recommendations, characterized by extended waiting times and elevated service failure rates (Wang et al., 2020a).

RL has recently exhibited significant potential in enhancing sequential decision-making processes within the travel and tourism domain, encompassing tasks such as attraction selection and tour planning (Lyu, Shen, & Zhang, 2022). Nevertheless, the attainment of customer satisfaction within the tourism industry poses numerous technical challenges (Zhu & Zhang, 2021). The expansive state and action space pose an initial challenge when employing Reinforcement Learning for the provision of tourism services (Sharma et al., 2021). An alternative approach is to implement a MARL framework for tourist service recommendations, treating each attraction as a distinct agent. The second challenge involves coordinating and cooperating in a large-scale system, where different service providers must collaborate to enhance recommendations. Cooperative efforts are indispensable for long-term optimization rather than individualized approaches (Suanpang et al., 2022b). Consequently, this manuscript advocates for the introduction of a bespoke centralized system aimed at fostering the assimilation of coordinated and cooperative policies among multiple service providers (Suanpang et al., 2022b).

The third challenge in providing tourism services arises from potential competition for future service demands, depicted in Figure 1. Finite service resources over time can lead to real-world competition at any service provider, causing issues like extended wait times and service unavailability. Anticipating the impact of future service requests is challenging. To address this, we employ a delayed access technique in our centralized system to incorporate competitive information. We transform our architecture during a training phase to enable decentralized execution of online recommendations, considering future requests. Lastly, a dynamic gradient reweighting technique is introduced, compelling service providers to balance multiple objectives and focus on poorly optimized ones for adaptive optimization steering.

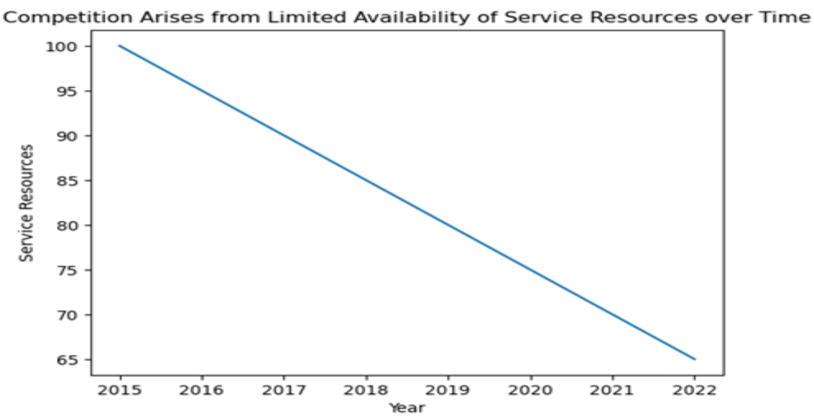

Figure 1: Competition Arises From a Limited Availability of Service Resources Over Time.

This scholarly work introduces a "multi-agent actor-critic framework" named Multi-Agent Spatio-Temporal Reinforcement Learning (MASTER). MASTER stands as a promising methodology facilitating agents to acquire decentralized policies within continuous spatio-temporal domains. This approach enables coordination among agents to collectively pursue a shared objective (Wang et al., 2020b). This research delves into the potential applications of the MASTER framework in the domain of tourism services. The objective is to optimize operational processes, customize recommendations, and enhance the overall tourist experience (Wang et al., 2020b; Zhang et al., 2022). In its entirety, this paper underscores the advantages of employing the MASTER framework within the tourism industry. It furnishes illustrations of how MASTER can be effectively utilized to elevate service quality and enhance the overall customer experience. Consequently, this investigation scrutinizes the potential of ITSRS to enrich tourism services, emphasizing its broader implications for the tourism sector, local communities, and the nation's profile as an eco-friendly travel destination. The study intricately examines the significance of tourism service recommendations, delineating the reciprocal benefits for both tourists and service providers. Additionally, it probes into the machine learning algorithms and data sources integral to generating personalized recommendations for individual tourists. The emphasis is on elucidating the transformative capacity of tourism service recommendations in reshaping the landscape of the travel industry.

This paper specifically seeks to explore the application of ITSRS in enhancing tourism services within Thailand, with a comprehensive examination of its extended ramifications for the tourism sector, local communities, and the country's image as a sustainable tourist destination. The study introduces and expounds upon the "MASTER" architecture as a recommended methodology for facilitating intelligent suggestions for tourist services.

This paper contributes by first framing the service recommendation problem as a MARL task, a novel approach for multi-objective intelligent service suggestions. Second, it introduces a decentralized execution and centralized training multi-agent actor-critic system. Third, it extends the centralized attentive critic concept to encompass multiple critics, addressing diverse optimization goals. A dynamic gradient updating approach is employed to adaptively influence the optimization direction, enhancing policy learning. Fourth, utilizing real-world datasets from renowned tourist locations, the study conducts comprehensive experiments, demonstrating the model's superiority over nine baselines in overall performance. Lastly, the system is implemented and tested with 400 samples to assess system satisfaction.

2. Review Literature

2.1 Tourism Services Schelduing

Leveraging optimization methodologies, such as genetic algorithms, for the creation of optimal schedules contingent upon customer preferences and service availability, machine learning techniques (Halder et al., 2023) and Multi-agent systems have also been applied to tourism service scheduling. Furthermore, reinforcement learning represents an alternative approach that has been employed in the scheduling of tourism services. Besides, Nawshin (2018) proposed a scheduling model that incorporates the influence of weather conditions on outdoor activities, while Zhou et al. (2020) advocated for a scheduling model that integrates the temporal and financial aspects of transportation. Other research has investigated advanced technologies, like virtual reality, in tourism service scheduling. These studies collectively highlight the potential of employing advanced techniques such as optimization, machine learning, multi-agent systems, and reinforcement learning in the scheduling of tourism services. Additional research is essential to assess the efficacy of these techniques in real-world contexts and to address practical challenges including scalability, robustness, and adaptability to evolving customer preferences and service availability.

2.2 Multi-agent Reinforcement Learning (MARL)

Foerster et al. (2017) suggested a MARL framework designed to acquire communication and cooperation skills in a decentralized fashion. The proposed methodology relies on deep reinforcement learning and incorporates a communication protocol facilitating information exchange among agents to coordinate their actions. The empirical investigation substantiates the efficacy of the proposed approach in effectively addressing a collaborative navigation problem within a simulated environment. Kumar et al. (2021) proposed a multi-agent deep reinforcement learning technique for the optimization of traffic signal control. The articulated method employs a decentralized actor-critic architecture to acquire the optimal traffic signal timing policy. Empirical findings from the study indicate that the proposed approach yields substantial reductions in travel time and queue length within a simulated traffic network. Whereas, Liu et al. (2020) Proposed a comprehensive reinforcement learning approach tailored for multiple agents in the context of tour suggestion. The suggested methodology adopts a centralized critic and decentralized actor architecture to acquire the optimal tour recommendation policy for each agent. In summary, MARL has exhibited considerable promise across diverse application domains, encompassing tourism service recommendation. Nevertheless, several challenges and avenues for future research persist in this domain, including concerns related to scalability, stability, and interpretability of MARL models.

2.3 Tourism Service Intelligent Recommendation System in Smart Cities Destination

2.3.1 Tourism Service Intelligent Recommendation System (TSIR)

The integration of TSIR systems within the context of smart city initiatives has constituted a significant area of scholarly exploration over recent decades. This endeavour has brought about a transformative influence on the manner in which tourists engage with urban destinations. Numerous research endeavours have scrutinized the complexities inherent in these systems, with the overarching objective of augmenting personalization and fostering user satisfaction throughout the travel experience. According to Suanpang et al. (2021) significant factors include the utilization of STDs, vacation experiences, satisfaction, and the desire to revisit. The influence of smart tourism impressions on return inclinations is notable. This study builds upon the earlier research conducted by our team on "Tourism Service Scheduling in Smart City Based on Hybrid Genetic Algorithm Simulated Annealing Algorithm." (Suanpang et al., 2022b). This study aimed to devise a novel hybrid genetic algorithm for optimizing tourism service problem-solving processes. The approach combines a gradient search technique with a simulated annealing algorithm, incorporating machine-based crossovers using order-based precedence preserving for offspring generation. Additionally, a simulated annealing neighbourhood searching technique was employed to enhance the algorithm's local exploitation capabilities and expand its applicability (Suanpang et al., 2022b).

2.3.2 Smart Cities Destination

Smart cities leverage advanced technologies and data-driven methodologies to enhance the quality of life for both inhabitants and visitors. Initiatives exemplified by smart cities like Suphanburi serve as noteworthy paradigms for other regions seeking to attain smart city status (Suanpang et al., 2022b). Central initiatives, encompassing the deployment of IoT devices, smart grids, and data analytics, have assumed a pivotal role (Suanpang et al., 2022b). The influence of smart city initiatives on the sustainability of Suphanburi has been substantial, particularly evident in noteworthy progress achieved in the realm of efficient waste management systems and energy conservation measures (Suanpang et al., 2022a). Moreover, there has been a notable enhancement in the quality of life for residents, exemplified by improved tourism services, diminished traffic congestion, and reinforced public safety meas. The region has executed diverse ICT initiatives in its transformation into a smart tourism destination. These initiatives involve the creation of mobile applications that provide real-time information concerning local attractions, events, and accommodations (Malek, Lim, & Yigitcanlar, 2021)

Yet, the transformation into a smart city in Suphanburi is not devoid of challenges. Issues pertaining to data security, privacy, and infrastructure development, as highlighted by (Suanpang et al., 2022a), remain significant concerns. A central challenge faced by Supanburi in its endeavour to evolve into a smart city revolves around the imperative for robust infrastructure. The essential upgrade of existing infrastructure is a key requirement for the seamless integration of smart technologies into Supanburi's urban landscape (Suanpang et al., 2021; Suanpang et al., 2022b).

2.5 Tourist’s Satisfaction of using Intelligent Recommendation System in Smart Cities Destination

2.5.1 Tourist Behaviors and Perceptions

Tourism behavior comprises two primary components: attitude and behavior (Hughes, 1991; Tyan, Yagüe, & Guevara-Plaza, 2020). "Attitude" pertains to the inclination to maintain a relationship with a product or service, while "behavioural" denotes the continuation of tourism activities towards a specific destination. Tourists' perceptions encapsulate their perspectives, insights, and preferences, encompassing their propensity to recommend the destination to others or plan future revisits (Morais & Lin, 2010). This facet is intricately linked to the subsequent hypothesis:

H1:*Tourist’ s behavior is positively related to the relationship with tourist’s perception.*

H2:*Tourist’ s behavior is positively related to the relationship with recommendation system value.*

2.5.2 Tourist Satisfaction

The ITRS enhances the tourism experience through the integration of information technology. This is achieved by providing real-time information about destinations and hospitality services during the planning phase, facilitating improved access to real-time information for tourists during their journey, and encouraging them to retrospectively engage with the experience through valuable feedback after the completion of the trip (Morais & Lin, 2010; Suanpang et al., 2021; Suanpang et al., 2022b). The anticipated outcomes of the TRS include an elevated tourism experience and heightened satisfaction, primarily through the delivery of personalized services. This entails providing information tailored to user profiles to assist in travel planning, as well as optimizing routes to economize on time, cost, and energy (Kiatkawsin, Sutherland, & Lee, 2020; Suanpang et al., 2021; Suanpang et al., 2022b). This conceptual alignment corresponds with the subsequent hypothesis:

H3: *Tourist' s perception is positively related to the relationship with recommendation system value.*

H4: *Recommendation system value is positively related to the relationship with overall satisfaction.*

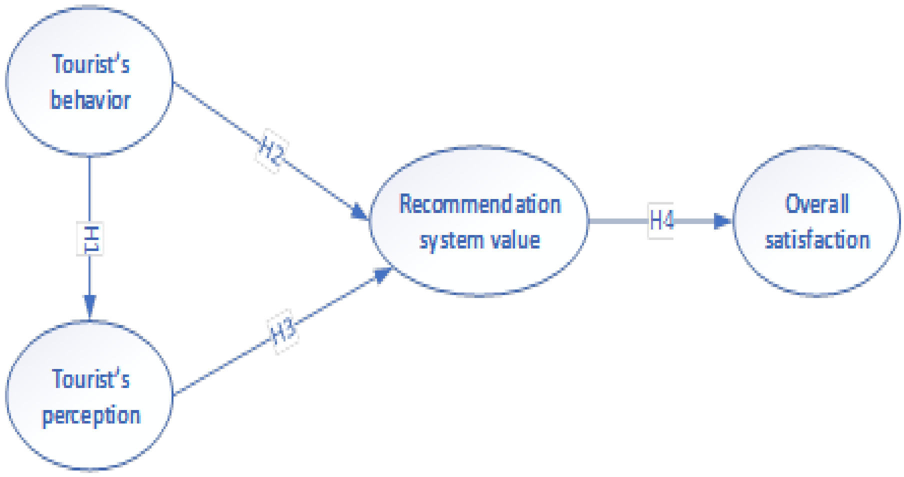

Figure 2. Hypothesis framework of user evaluation the optimizing ITRS by MARL for smart cities destination.

Figure 2 delineates the hypothesis framework for the user evaluation of the tourism service recommendation system optimization by MARL intended for smart city destinations. The framework encompasses four variables: tourist behaviour, tourist perception, recommendation system value, and overall satisfaction.

3. Methodology

3.1 Research Framework

The study's configuration, as depicted in Figure 3, employs the framework of the System Development Life Cycle (SDLC). Elaborations on this are expounded upon in the subsequent sections.

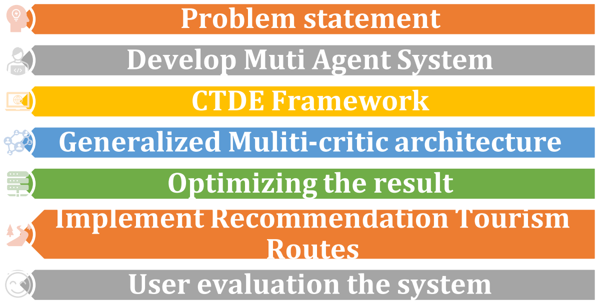

Figure 3: Research Framework.

3.2 MARL Development

Figure 4 depicts the MARL framework proposed in this paper for TSR, facilitating decentralized collaboration and learning among agents. The framework comprises a centralized critic network and decentralized actor networks. The centralized critic network computes the system's value function based on inputs from all agents. Each agent possesses its own actor network, which learns to generate recommendations using its observations and the global state. Experimental results demonstrate the superior performance of the proposed framework in terms of recommendation accuracy and diversity, effectively capturing complex interactions between agents to generate optimal recommendations tailored to individual preferences needed of the user.

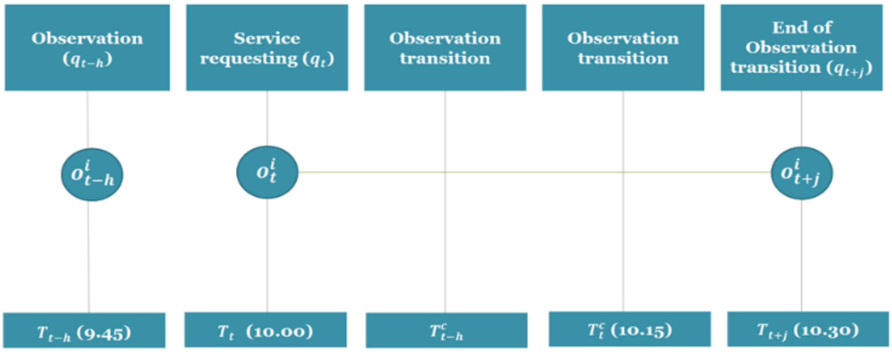

Figure 4: Transition Sate in MARL.

3.2 Centralized Training, Decentralized Execution

The "centralized training, decentralized execution" method is employed in MARL to foster the learning of agents in coordinating their policies and adapting to dynamic environments. In the domain of tourism services, this approach comprises three primary components: a centralized attentive critic, a mechanism for integrating information regarding future competition, and a decentralized execution process.

3.3 Centralized Attentive Critic

The proposed approach enhances tourism service recommendations through a multi-agent framework with a centralized attentive critic. Agents, viewed as nearby tourism service providers, are activated based on proximity to the request. An attention mechanism integrates information from active agents, quantifying their influence. Utilizing states, joint actions, and future information, each agent's policy is updated iteratively through the gradient of the expected return. The centralized attentive critic considers collective information, promoting coordinated and cooperative policy learning. This optimization aims to improve tourism service recommendations by fostering synergistic learning among agents.

3.4 Integrating Future Tourism Service Competition

We propose utilizing a centralized attentive critic with a delayed access strategy to integrate future competition information. This allows agents to learn policies based on future knowledge, enhancing decision-making beyond current information. Specifically, when a customer requests a service, transition data access is deferred until future competition details are available. Accurate counts of available service spots for each subsequent time interval are extracted, and a fully connected layer integrates this future competition information into the centralized attentive critic model. This approach enhances our ability to anticipate and address future competition for tourism services, leading to more efficient and satisfying customer experiences. Integrating potential competition into our decision-making improves customer satisfaction and reduces the risk of service failure.

3.5 Decentralized Execution

The execution process of tourism services is entirely decentralized, wherein each agent relies solely on its own observations to make decisions. Specifically, when a tourism request qt is initiated, the agent responsible for charging station $c\ i \in C\ a\ t$ takes action $a\ i\ t$ based on its individual observation $o\ i\ t$, as delineated below:

$$a\ i\ t = \boldsymbol{b}\ i\ () \tag{1}$$

Subsequently, the tourism request qt is directed to the agent exhibiting the highest action value among all agents in $C\ a\ t$. This streamlined execution procedure does not necessitate access to future tourism competition information, and the system retains fault tolerance even in instances where some agents may encounter failures.

3.6 Multiple Objectives Optimization

The goal of the tourism service recommendation task is to minimize the collective waiting time, mean cost, and customer satisfaction rating. These objectives are consolidated into two distinct reward functions: the overall waiting time reward function denoted as rcwt, and the average cost and customer satisfaction reward function denoted as rcp. A tourism service can enhance its business performance across multiple objectives by strategically allocating different weights to various facets.

Nevertheless, this strategy may not consistently demonstrate efficiency and may yield biased solutions. To enhance the efficacy of the tourism service, a dynamic gradient reweighting strategy can be implemented to adapt to diverse training stages and harmonize priorities. This technique extends the centralized attentive critic to multiple critics, where each critic corresponds to a distinct objective. Two centralized attentive critics can be trained—one for the expected returns of rewards in tourism service and another for the expected returns of rewards in customer satisfaction. The convergence degree of these two objectives can be gauged by introducing two centralized attentive critics linked to two objective-specific optimal policies concerning rewards in tourism service and customer satisfaction. The gap ratio between the multi-objective policy and objective-specific optimal policy can be computed and employed to reinforce poorly optimized objectives with a larger update weight or fine-tune well-optimized objectives with a smaller step size. The dynamic update weights can be determined through the Boltzmann SoftMax function, adjusting the step size of the two objectives.

3.7 Multi-Agent Spatio-Temporal Reinforcement Learning (MASTER)

MASTER represents a learning framework designed for multi-agent environments, wherein agents possess the capability to perceive and act within a continuous spatio-temporal domain. The primary innovation of MASTER lies in its approach to handling this continuous spatio-temporal domain. It employs neural networks to depict the value function and policy of each agent, enabling continuous action selection and value estimation, in contrast to conventional methods that rely on static operations. Thus, MASTER emerges as a distinctive framework tailored for learning in multi-agent settings with continuous spatio-temporal dynamics. The algorithm for MASTER is detailed as follows:

1. Each agent perceives its localized spatio-temporal environment.
2. Each agent chooses an action based on its policy and the observed environment.
3. Each agent executes the chosen action, transitioning to the subsequent spatio-temporal state.
4. Each agent obtains a reward contingent upon the collective state and action of all agents.
5. Each agent retains the experiential tuple (state, action, reward, next state) within its individual local replay buffer.
6. Randomly extract a mini-batch of experiential tuples from the replay buffer of each agent.
7. Calculate the loss function for each agent's neural network using the sampled experiential tuples and subsequently backpropagate the gradients.
8. Revise the neural network weights of each agent by applying the optimizer.
9. Harmonize the neural network weights of each agent with the central parameter server.

Iterate through steps 2 to 3 until convergence or a predefined maximum number of time steps is attained. The fundamental concept behind MASTER is to empower each agent to glean insights from its individual experiences while concurrently coordinating with other agents to attain a shared objective.

3.8 System Implications and Evaluation from User

The implementation of the recommendation system transpired over a span of three months, encompassing 10 hotels and 10 restaurants situated within Suphanburi smart city, Thailand. The target population comprised Thai national visitors. The sampling methodology employed was convenience sampling, specifically adopting a non-probability sampling approach. In accordance with Cochran (1977), the sample size persisted at over 400 participants, employing a 95% confidence level ($\alpha = 0.05$) for each participant.

The questionnaire was structured into three sections. The initial segment addressed the demographics of the sample, encompassing information related to age, gender, educational background, employment, and income. The second section comprised sixteen questions evaluating the proposed strategy for optimizing tourist company operations (refer to Appendix I). Subsequently, the satisfaction section featured three closed-ended questions. Data analysis was conducted using LISREL 9.0 in conjunction with SPSS.

4. Result

4.1 Optimizing Tourism Service Recommendation System in Smart Cities Destination

To evaluate the efficacy of our proposed "tourism service recommendation system" based on multi-agent reinforcement learning, the researchers conducted experiments utilizing real-world tourism service data. The performance comparison involved five distinct algorithms: Real, Random, DQN, DDPG, and MADDPG.

The evaluation of the tourism service recommendation system encompassed four key metrics: Mean Wait Time (MWT), employed to gauge system efficiency by computing the average time users spent waiting for a recommended service, where a lower MWT signifies a more efficient system with reduced wait times. Mean Price (MP) was utilized to assess the cost of recommended services, with a lower MP indicating more budget-friendly and appealing services to users. Failure Rate (FR) served to evaluate the system's reliability, where a higher FR indicates less dependable service, potentially dissuading user adoption. Although Total Service Failures (TSF) is not directly applicable to tourism service recommendation, a comparable metric like Total Travel Cost Savings (TTCS) could be utilized to assess the economic benefits of employing the system for travel planning. In summary, these metrics collectively provide a comprehensive evaluation of the effectiveness of the tourism service recommendation system.

The outcomes demonstrated the superiority of MARL-based methods over random and traditional approaches, underscoring the efficacy of employing MARL in tourism service recommendation. Its ability to adapt to user behaviour and preferences enables the generation of personalized recommendations, better aligning with user needs.

The Deep Q-Network (DQN) algorithm, a deep reinforcement learning technique, is employed for acquiring the optimal Q-value function. In our study, we adopted DQN as a methodology for service recommendation. In the training of agents, DQN was implemented within a centralized training framework, wherein a singular agent acquired the optimal service recommendation policy applicable to all users. The state space encompassed user preferences and service features, while the action space comprised the recommended services (refer to Figure 5).

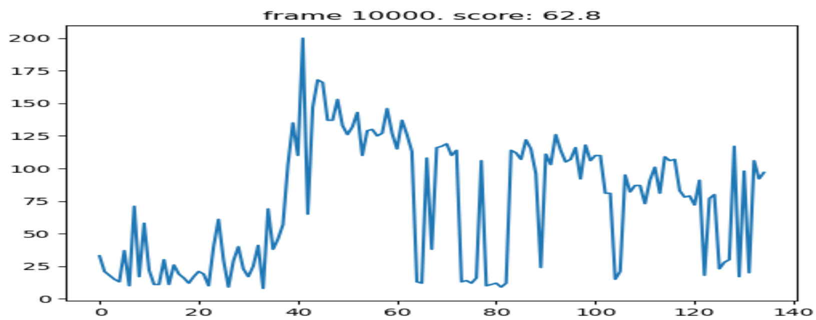

Figure 5: Average Rewards Over Time in DQN.

The investigation employed the Deep Deterministic Policy Gradient (DDPG) algorithm within a decentralized training framework. The state space incorporated user preferences and service features, while the action space comprised recommended services. The experimental results indicated that the DDPG algorithm exhibited favourable outcomes, with a mean customer waiting time (MCWT) of 14.81 and a mean customer preference (MCP) of 1.71. However, the algorithm exhibited a notable TSF rate of 12,472, implying that the recommended services did not consistently align with user expectations. Conversely, the DQN algorithm demonstrated promising outcomes, yielding a MCWT of 22.13 and a mean customer preference (MCP) of 1.65. Nevertheless, it exhibited a relatively high TSF rate of 8,813, suggesting occasional mismatches between the recommended services and user expectations (refer to Figure 6). Additionally, the DDPG algorithm was applied as an approach for service recommendation. DDPG, an actor-critic algorithm, amalgamates aspects of both value-based and policy-based reinforcement learning, making it well-suited for problems with continuous action spaces frequently encountered in real-world service recommendation scenarios. The DDPG algorithm demonstrated relatively positive results in our experiment, with a MCWT of 14.81 and a MCP of 1.71. However, it exhibited a notable TSF rate of 12,472, indicating occasional deviations from user expectations in the recommended services.

Lastly, the researchers employed the MADDPG algorithm for service recommendation. The outcomes from the MADDPG algorithm closely resembled those of the DDPG algorithm, exhibiting a MCWT of 13.95 and a MCP of 1.64. However, the TSF rate was marginally higher at 13,261, indicating occasional discrepancies between the recommended services and user expectations. In summary, our experimentation illustrated that MADDPG can serve as a viable approach for tourism service recommendation within a multi-agent framework. Nonetheless, there remains scope for refinement in terms of recommendation accuracy and the system's capacity to align with user expectations.

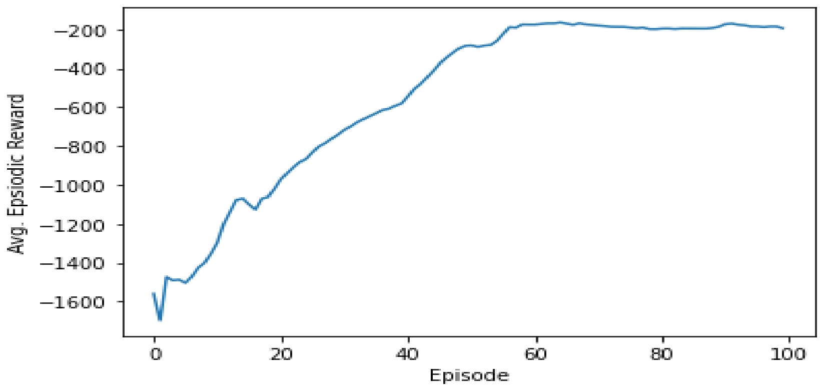

Figure 6: Average Rewards Over Time in DDPG.

Moreover, the MADDPG algorithm demonstrated comparable outcomes to the DDPG algorithm, displaying a MCWT of 13.95 and a MCP of 1.64. However, it exhibited a slightly elevated TSF rate of 13,261, suggesting occasional disparities between the recommended services and user expectations. In summary, our experimentation indicated that MADDPG holds promise as an effective approach for tourism service recommendation within a multi-agent setting as shown in Figure 7.

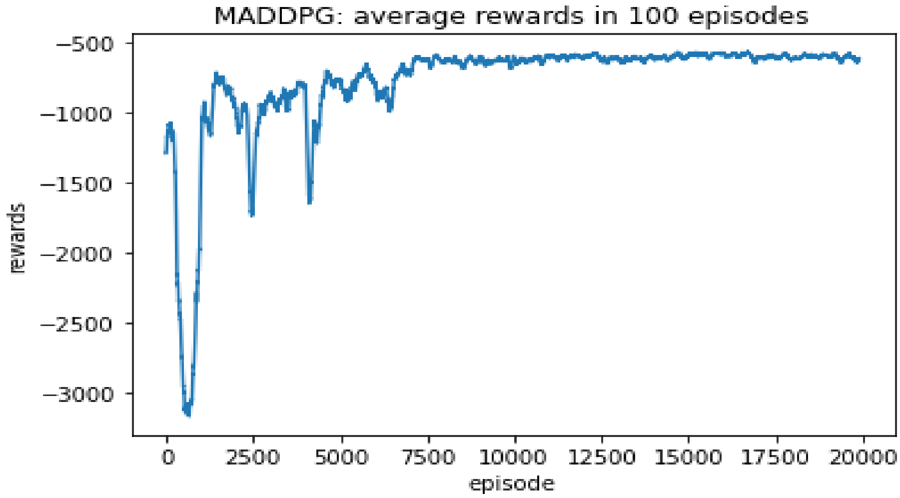

Figure 7: Average Rewards Over Time in MADDPG.

Table 1 presents the outcomes of our assessment of five algorithms (Real, Random, DQN, DDPG, and MADDPG). All algorithms, except for Random, outperformed the Real algorithm. The Random algorithm exhibited a higher MCWT of 41.82 minutes, indicating extended wait times for users, and a higher TSF rate of 59.1%, signifying a substantial service failure rate in recommending services. The Real algorithm displayed a high MCWT of 26.3 minutes, suggesting significant wait times for users, and a high SFT of 28.1%, indicating a notable percentage of service recommendations resulting in failure. Overall, the results imply that the DQN, DDPG, and MADDPG algorithms surpass the Real and Random algorithms in terms of MCWT, CFT, and TSF, potentially enhancing user experience and increasing user adoption of recommended services.

Table 1: Performance Evaluation of the Algorithms MCWT, MCP, TSF, and SFT.

Algorithm	MCWT	MCP	TSF	SFT
Real	26.3	1.85	-592	28.1%
Random	41.82	1.91	-537	59.1%
DQN	22.14	1.65	8713	8.37%
DDPG	14.81	1.71	12472	3.83%
MADDPG	13.95	1.64	13251	3.21%

4.2 Implication Tourism Service Recommendation System in Smart Cities Destination

The optimization of the tourism recommendation system for the smart city destination of Suphanburi was accomplished through the integration of MARL techniques. This integration was implemented across both a web-based system and a mobile application. The development of the system consisted of two primary components: the tourism database system of Suphanburi Province, administered using pgAdmin for PostgreSQL, and the web server component utilizing Apache + PHP 7. The web development process was facilitated using the Sublime program, acting as the interface for connecting travel-related websites with the accessible databases at https://mapedia.co.th/suphan-travel/ (Refer Figure 8).

Figure 8: Intelligent Tourism Service Recommendation System in Smart Cities Destination.

4.3 Systems Implimetnation and User Evaluation

4.3.1 Demographic Information

Here are the demographic characteristics of the participants.

(1) Demographic details indicate a predominant female tourist population, comprising 317 individuals. The age distribution primarily falls within the 45-59 years bracket, accounting for 122 individuals (28.00%). Among the participants, 122 individuals (28.00%) identified as company/state enterprise employees. In terms of income, 129 individuals (32.25%) reported an income range of 10,001-20,000 Baht.

(2) Tourist behaviour analysis reveals that a substantial portion of tourists, totalling 237 individuals (59.25%), visited Suphanburi Province accompanied by their families or companions. The predominant pattern observed was an average stay of 2 nights per trip, reflecting the highest frequency with 176 individuals (44.00%). In terms of lodging preferences, hotel-type accommodations were favoured by the majority, constituting 175 individuals (43.25%). Additionally, a prevalent choice was accommodations priced between 1,000-1,500 Baht per night, as indicated by 134 individuals (33.50%).

4.3.2 Structural Equation Modeling

Tourist behaviour demonstrates a significant positive impact on both Tourist's Perception and Tourism Value, with effect sizes of 0.995 and 0.550, respectively. Furthermore, Tourist's Behaviour has an indirect influence on Tourism Value through the mediating variable Tourist's Perception, indicating an indirect effect size of 0.403. It also affects overall satisfaction through the mediating variable System Value, with an indirect effect size of 0.512 (refer to Figure 9).

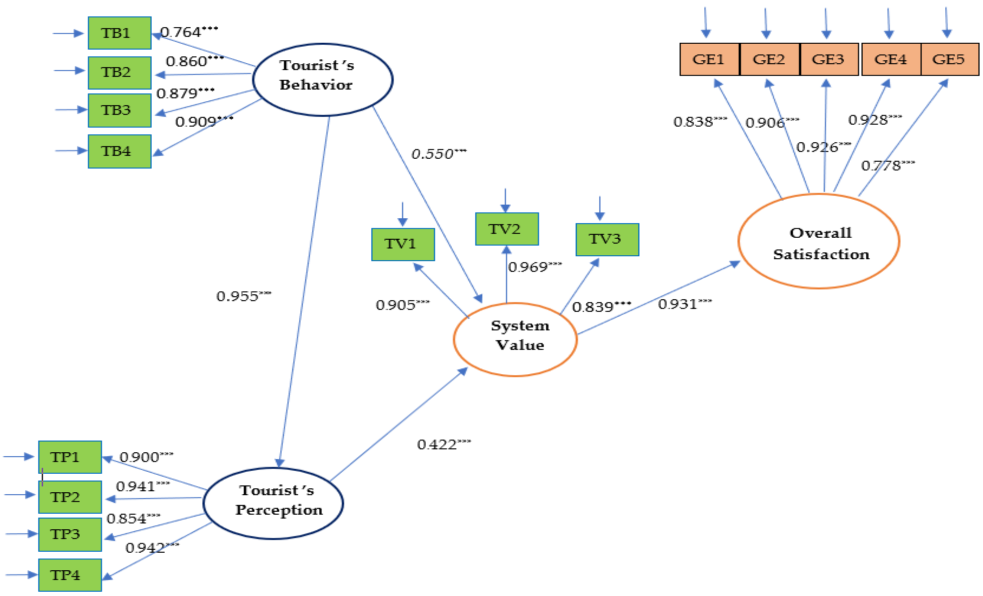

Figure 9: The User's Total Happiness with Adopting Optimization Tourism Suggestions has been Assessed Using a Causal Connection Model.

Additionally, Tourist's Perception exhibits a direct and positive impact on System Value, with an effect size of 0.422. Moreover, it indirectly influences Overall Satisfaction through the mediating variable Tourism Value, demonstrating an indirect effect size of 0.393. System Value is shown to have a direct positive influence on Overall Satisfaction, emphasizing its pivotal role in shaping tourists' satisfaction levels. A comprehensive depiction of these intricate relationships is presented in Table 3.

Table 3: The Correlation Coefficient.

Latent variables	Tourist's Behavior			Tourist's Perception			System Value		
	TE	DE	IE	TE	DE	IE	TE	DE	IE
Tourist's Perception	0.955	0.955	-	-	-	-	-	-	-
System Value	0.953	0.550	0.403	0.422	0.422	-	-	-	-
Overall Satisfaction	0.887	-	0.887	0.393	-	0.393	0.931	0.931	-

Total Effects (TE), Direct Effects (DE), and Indirect Effects (IE) ***p-value<0.001

Examining tourist behaviour, value assessment, purchase decision, and destination selection collectively account for 82.70%, 77.20%, and 74.00%, respectively, of the variance. In the domain of tourist perception, information processing, ownership perception, and personalization processes explain 88.80%, 80.50%, and 81.10% of the variation. Regarding overall satisfaction, personalization processes, emotional stimulation, and financial considerations constitute the most significant factors, elucidating 86.10%, 85.80%, and 82.10% of the variance. Additionally, tourist behaviour contributes to 91.20% of the variation in tourist perception, while both tourist behaviour and tourist perception jointly account for 92.50% of the variation in system value. System value, in turn, clarifies 86.60% of the variance in overall satisfaction (Table 4).

Table 4: Model Fit.

		Standardized Regression Weights (β)	***se***	***t***	R^2
Tourist's Behavior	TB1	0.764	-	-	0.5840
	TB2	0.860	0.060	18.898***	0.7400
	TB3	0.879	0.060	19.411***	0.7720
	TB4	0.909	0.058	20.265***	0.8270
Tourist's Perception	TP1	0.900	-	-	0.8110
	TP2	0.941	0.031	32.319***	0.8850
	TP3	0.854	0.039	25.154***	0.7290
	TP4	0.942	0.033	32.489***	0.8880
System Value	TV1	0.905	-	-	0.8200
	TV2	0.969	0.028	36.453***	0.9400
	TV3	0.839	0.037	24.550***	0.7040
Overall Satisfaction	GE1	0.838	-	-	0.7040
	GE2	0.906	0.041	24.395***	0.8210
	GE3	0.926	0.042	25.431***	0.8580
	GE4	0.928	0.041	25.495***	0.8610
	GE5	0.778	0.045	18.885***	0.6060

****p-value <.001*

The examination of the model's goodness of fit indices reveals favorable results: χ^2 = 43.753, df = 32, χ^2/df = 1.367 (below 2, indicating good fit), p-value = 0.081, Goodness of Fit Index (GFI) = 0.980, Adjusted Goodness of Fit Index (AGFI) = 0.975, Comparative Fit Index (CFI) = 0.995, Normed Fit Index (NFI) = 0.985 (all above 0.95, indicating good fit), Root Mean Square Residual (RMR) = 0.020, and Root Mean Square

Error Approximation (RMSEA) = 0.023 (below 0.05, indicating good fit). Details are outlined in Table 5.

Table 5: Examination of the Model Conformity Index.

Statistics	Criteria	Value	Pass
χ^2/df	> 2.00	1.367	Pass
p-value	< .05	0.081	Pass
GFI	< .95	0.980	Pass
AGFI	< .95	0.975	Pass
CFI	< .95	0.995	Pass
NFI	< .95	0.985	Pass
RMR	>.05	0.020	Pass
RMSEA	>.05	0.023	Pass

Table 6 presents the outcomes of hypothesis testing (H1-H4), indicating the following results: H1: Tourist's behaviour exhibits a positive and significant relationship with tourist's perception at a significance level of 0.001. H2: Tourist's behaviour demonstrates a positive and significant association with recommendation system value at a significance level of 0.001. H3: Tourist's perception is positively related to recommendation system value with a significance level of 0.001. H4: Recommendation system value shows a positive and significant relationship with overall satisfaction at a significance level of 0.001.

Table 6: Hypothesis Testing.

Hypothesis	Value	Sig
H1	0.955***	Sig 0.001
H2	0.550***	Sig 0.001
H3	0.422***	Sig 0.001
H4	0.931***	Sig 0.001

****significant at the 0.001 level*

5. Discussion and Implications

This study introduces an innovative approach to tourism service recommendation using MARL, addressing the challenge of providing personalized suggestions to accommodate diverse tourist preferences. The findings reveal that the MADDPG algorithm outperforms other methods, achieving the shortest MCWT of 13.95 minutes, the lowest SFT of 3.21%, indicating higher reliability, and the highest TSF of 13,261. These results highlight the MADDPG algorithm's efficiency in learning user preferences, offering personalized recommendations, enhancing user experience, and boosting customer satisfaction by fostering cooperative behaviour among multiple agents. Studies conducted by Rashid et al. (2020) have identified the practical applications of MADDPG in real-world domains, particularly in smart city destinations. Additionally, research conducted by Sunehag et al. (2017) delves into the algorithm's implementation in traffic signal control, showcasing its efficacy in optimizing traffic flow within urban environments.

The outcomes of our investigation reveal that the MADDPG algorithm stands out as the most effective choice for our proposed tourism service recommendation system grounded in MARL. This algorithm exhibits proficiency in delivering dependable, efficient, and cost-efficient services to tourists. The heightened performance of MADDPG can be attributed, in part, to its capacity for learning and adapting to evolving user preferences and behaviours. By employing a centralized critic and decentralized actors, this algorithm adeptly learns from the interactions among agents and the environment, showcasing effectiveness in managing intricate and dynamic scenarios. Furthermore, the utilization of multi-agent reinforcement learning contributes to its ability to discern interactions and dependencies between diverse agents, enabling the provision of personalized recommendations to individual users (Suanpang et al., 2021).

Moreover, the behaviour of tourists manifests a direct and positive impact on both the perception of tourists and the value of the system. Furthermore, tourist behaviour indirectly shapes tourism value through the mediating variable of tourist perception, and it affects overall satisfaction through the mediating variable of system value. The general satisfaction derived from utilizing this system is substantial, and there is an intention expressed to revisit this destination in the future. The outcomes of this study contribute to the creation of personalized travel recommendations. In alignment with related studies, such as Suanpang and Jamjuntr (2023) systems are designed to analyse user preferences and historical data to furnish tailored suggestions, thereby enhancing the overall travel experience. Liu et al. (2020) indicated that recommendations tailored to the context ensure that tourists receive suggestions aligned with their current situations, enhancing the relevance and enjoyment of their experiences.

This paper introduces a novel tourism service recommendation system grounded in MARL, employing the MADDPG algorithm. The system offers various potential contributions to the tourism industry (Abdellatif et al., 2021). The proposed tourism service recommendation system, based on MARL utilizing the MADDPG algorithm, has the potential to significantly enhance smart city destinations. This system offers multifaceted contributions to the tourism industry and the broader realm of multi-agent reinforcement learning. Primarily, it provides personalized recommendations to tourists, enhancing the efficiency and optimization of the tourism experience. Moreover, it promotes increased engagement with tourism services, potentially yielding diverse environmental and economic benefits. While the direct environmental impact is context-dependent, sustainable management can positively influence local economies and encourage environmentally conscious practices. Additionally, by enhancing service quality and visitor satisfaction, the system enhances the competitiveness of the tourism sector. The utilization of the MADDPG algorithm and the comprehensive evaluation of diverse algorithms contribute to the advancement of sophisticated recommendation systems, promising applications across various domains beyond tourism.

The contributions were analyzed from a variety of studies, including personalized recommendations (Aldayel et al., 2023), collaborative planning (Liu et al., 2024), hotel room pricing and numerous other domains (Zaizi, Qassimi, & Rakrak, 2023). Analysing these works, our review offers valuable insights into the potential of MARL employing the MADDPG algorithm to tackle intricate and dynamic issues across diverse contexts (Kuo, Chen, & Keng, 2021). Moreover, this investigation introduces a tourism service recommendation system, and its associated research holds the potential to contribute to the progress of the tourism industry and the wider domain of MARL (Sarkar et al., 2023; Zaizi et al., 2023). The examined studies underscore the increasing interest in MARL and its capacity to augment conventional methodologies across diverse domains. As a result, the insights derived from this literature review can guide the creation of advanced and effective recommendation systems in tourism and other sectors, offering valuable knowledge to researchers and practitioners alike (Aldayel et al., 2023).

6. Conclusion And Future Directions

In this study, we've introduced an innovative approach to tourism service recommendation, utilizing MARL with a focus on the MADDPG algorithm. Tackling the challenge of providing personalized recommendations to tourists with diverse preferences, our system employs a Multi-Agent System (MAS) where each agent represents a tourism service provider. Leveraging the collective intelligence of these agents enhances recommendation quality. The Centralized Training with Decentralized Execution (CTDE) framework, a hybrid model combining centralized training and decentralized decision-making during execution, was introduced. User evaluation revealed a significant impact on tourist behaviour and preferences, with high overall satisfaction and intentions of revisiting the destination. This aligns with previous studies emphasizing user satisfaction in tourism recommendation systems. Our proposed tourism service recommendation system based on MARL with the MADDPG algorithm holds immense potential.

Prospective research endeavours could concentrate on refining the performance of the MADDPG algorithm to amplify user experiences. Our investigation robustly advocates for the MADDPG algorithm as the most efficacious selection for our envisaged Tourism service recommendation system grounded in MARL. It accentuates the significance of methodically evaluating algorithms in tourism service recommendation systems to discern optimal strategies. Subsequent research initiatives may delve into fine-tuning the MADDPG algorithm, striving to elevate user experiences.

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Author Contributions

Conceptualization, P.S.; research Design, P.S.; literature review, P.S. and P.J.; methodology, P.S. and P.J.; algorithms, P.S. and P.J.; software, P.S. and P.J.; validation, P.S. and P.J.; formal analysis, P.S. and P.J.; investigation, P.S. and P.J..; resources, P.S.; data curation, P.J.; writing original draft preparation, P.S. and P.J.; writing review and editing, P.S. and P.J..; visualization, P.S..; supervision, P.S..; project administration, P.S.; funding acquisition, P.S.

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Appendix A

Appendix I

Variable of the Evaluation

TB1	Tourist behavior
TB2	Destination Selection: The process of choosing a travel destination.
TB3	Purchase Decision Making: The decision-making process involved in buying travel-related products or services.
TB4	Value Evaluation: The assessment of the worth or value of travel experiences in relation to the cost incurred.
TP1	Personalization Processes: Individualized processes that cater to personal preferences and needs.
TP2	Ownership Perception: Emotional and psychological processes associated with feeling a sense of ownership or belonging.
TP3	Thought-Stimulating Processes: Mental processes that encourage creative thinking and decision-making.
TP4	Information Processing: The mental processes involved in acquiring, interpreting, and understanding travel-related information.
TV1	Financial Considerations: Evaluating and managing financial aspects of travel, including budgeting and spending.
TV2	Destination Image: Perception and impression of a travel destination.
TV3	Technology Promotion in Tourism: The use of technology to promote and enhance tourism experiences.
GE1	Tourists believe that RS systems will help create excellent travel experiences.
GE2	Tourists believe that RS systems are user-friendly.
GE3	Tourists are of the opinion that RS systems will stimulate greater tourist engagement.
GE4	Tourists anticipate that RS systems will become more popular in the future.
GE5	Tourists believe that RS systems can create value, distribute income, and genuinely contribute to community development.