Pakistan Journal of Commerce and Social Sciences
2026, Vol. 20(2), 296-321
https://doi.org/10.64534/Commer.2026.676

Predictive AI Crowd-Management Messaging and Its Influence on Perceived Control, Stress Reduction, Temporal Satisfaction, and Destination Loyalty

Umer Zaman
Endicott College of International Studies, Woosong University, Daejeon, Republic of Korea
Email: umerzaman@endicott.ac.kr

Article History

Received: 11 Mar 2026 Revised: 16 June 2026 Accepted: 24 June 2026 Published: 30 June 2026

Abstract

This study investigates the influence of predictive AI crowd-management messaging on tourists' psychological and behavioral responses in crowded destinations. Drawing on the Stimulus–Organism–Response (S–O–R) framework, the study examines how predictive and data-driven crowd-management messages shape perceived control, stress reduction, temporal satisfaction, and destination loyalty. A quantitative cross-sectional design was employed using purposive sampling. Data were collected from 265 tourists who had recently visited destinations offering digital or smart tourism information services. The respondents were selected from tourism destinations utilizing AI-enabled crowd-management and informational systems. Established measurement scales adopted from prior studies were used, and data were analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS. The findings reveal that predictive AI crowd-management messaging significantly enhances tourists' perceived control, which subsequently reduces stress and improves temporal satisfaction. Temporal satisfaction emerged as a strong predictor of destination loyalty. Furthermore, the results support a serial mediation mechanism in which predictive AI crowd-management messaging enhances perceived control, leading to stress reduction, which subsequently increases temporal satisfaction and ultimately strengthens destination loyalty. The study extends smart tourism literature by integrating AI-based crowd-management communication with tourists' cognitive, emotional, and evaluative processes. The findings suggest that destinations can leverage predictive AI communication to enhance tourists' sense of control, reduce stress, improve time-related experiences, and foster long-term destination loyalty.

Keywords: Predictive AI, crowd management, perceived control, stress reduction, temporal satisfaction, destination loyalty.

1. Introduction

The rapid increase in numbers of visitors travelling around the world and the growing density in popular travel destinations have led to growing concerns about crowding and congestion, visitor safety and experience quality (Wu et al., 2025). Overload can also have a negative impact on tourist satisfaction, on the destination image and on the sustainability of destination management, especially in the case of high traffic levels in the attraction, which has become a major challenge for destination managers and is determined by management of visitor flows (Raizada, 2025). Historically, crowd management was achieved through reactive strategies like manual interventions, physical monitoring, and real-time operational interventions. With the advent of smart tourism technologies, however, the monitoring and management of tourist movements have been completely revolutionized (Alafif et al., 2025). Smart tourism ecosystems combine information and communication technologies, big data analytics, mobile applications and artifical intelligence (AI) for the improvement of destination management and visitor experiences (Gretzel et al., 2015). These technologies offer the opportunity for destinations to provide information when it is needed, to make their services more efficient, and to facilitate informed decision making by tourists.

The potential of smart tourism systems is further amplified by recent developments of AI that can be integrated into the system (Mehraliyev et al., 2019). Instead of simply providing up-to-the-minute data, AI systems can predict how many people will be at a location at a given time and send out proactive messages to the people (Yi Wang et al., 2025). As opposed to just giving current data, AI-powered predictive systems can anticipate the quantity of individuals at a location at a particular moment and relay proactive info to visitors (Alsharif et al., 2024). Predictive crowd-management messages can help tourists make alternative travel plans, choose alternative routes and avoid congestion even before it happens. The benefits of technology-supported information services on travel planning, convenience and decision making, as well as reducing travel experiences' uncertainties have been shown in previous research (Li et al., 2017; Ngan et al., 2025). Research on crowding and congestion also indicates that crowd conditions without management typically have negative emotional consequences, lower satisfaction and decrease revisit intentions. In response, a growing number of destinations are turning to predictive AI communications systems to optimise their operations and enhance the guest experience.

In addition to the potentially operational advantages, predictive AI crowd-management messaging can also impact tourists' psychological states and behavioral outcomes (Novera et al., 2022). For a long time, tourism educators have emphasized the role of perceived control, emotional responses and satisfaction in defining visitor experiences and post-visit perceptions (Mohanty et al., 2026). A sense of control enables tourists to feel competent in coping with the uncertain situations, and lower stress levels result in more positive experiences of tourists. In addition, the assessment of the use of time during a trip, called

temporal satisfaction, has been determined as one of the key factors influencing general satisfaction and loyalty of tourists (Shin et al., 2025). While several studies have investigated the role of technology in tourism services, perceived crowding, tourists' emotions, and destination loyalty separately, they have not been combined in a single model (Strålman, 2025).

Even though the use of AI in DM is on the rise, there are still some key research gaps to be addressed. First, most studies are limited to real-time information systems and not predictive AI-based crowd-management messaging, which foresees the nature of crowds (Macriga et al., 2024). Second, previous studies have mainly focused on technology adoption and intentions to use, with fewer studies examining the psychological processes that mediate the effects of AI-driven communication on tourist experiences (Alturki et al., 2026). Third, the connection between predictive AI crowd-management messaging and destination loyalty is still relatively unstudied, especially the sequential cognitive and affective processes that could account for this connection (Chua et al., 2025). Loyalty is a crucial measure of tourism competitiveness and sustainability, so it is important both theoretically and practically to understand the principles underlying destination loyalty.

This study aims to answer this research question:

- In what way does AI Crowd Management Messaging affect perceived control, reduce stress and enhance tourists' temporal satisfaction, thereby affecting their destination loyalty?

Based on Stimulus–Organism–Response (S–O–R) model, this research proposes that crowd management messaging, using predictive AI, is an environmental stimulus that activates the tourists' internal cognitive and emotional reaction, which further drives behavioral response. That is, it suggests that predictive AI crowd-management messaging can improve the sense of control, thereby lowering stress, temporal satisfaction, and ultimately boosting destination loyalty. In order to examine this mechanism, the data were gathered from tourists who have the experience of using digital and smart tourism information services, and the proposed relationships were analyzed by Partial Least Squares Structural Equation Modeling (PLS-SEM).

The following are the contributions of this study to the literature of smart tourism: The following are a few contributions that this study makes to the literature on smart tourism: First, it takes existing knowledge to the next level by studying predictive AI crowd-management messaging instead of more traditional real-time information services. Second, it unites cognitive, emotional, and judgmental elements into an overall model of the effects of AI-assisted communication on tourists to deliver a more complete picture of its effects on tourists' behavior. Third, it presents the concept of temporal satisfaction as an important mechanism between technological interventions and destination loyalty. The results have important implications for researchers and practitioners. On a conceptual level, the research contributes to the use of the S–O–R model in AI-powered tourism settings. On a practical level, it offers recommendations for destination managers looking to create a system of

predictive communication that will not only help to manage a crowd but also positively influence tourist psychology and travel experience and, ultimately, tourist loyalty to the destination.

2. Literature Review

2.1 Predictive AI Crowd-Management Messaging

Predictive AI crowd-management messaging refers to the use of artificial intelligence, machine learning algorithms, sensor networks, and big-data analytics to forecast future crowd densities, congestion hotspots, visitor flows, and potential bottlenecks within tourism destinations (Macriga et al., 2024). In principle, it can be taken to be the transition to proactive rather than reactive information systems, in which destinations are not only reporting real-time conditions, but anticipating future congestion and recommending responsive measures like alternative routes or off-peak times (Chang et al., 2024). Most of the literature on smart tourism and intelligent transportation system points out that predictive information minimizes uncertainties, improves situational awareness and promotes effective decision-making among tourists (Elshaer et al., 2024). Such systems act as intellectual supplements that enable tourists to use intricate environments by converting unprocessed information to customized and timely information (W. Liu et al., 2025). Researchers are convinced that in the consideration of such messaging as true, topical and apt in time, the visitors see it as a value addition service that influences their overall experience and destination competence and innovativeness perceptions.

2.2 Perceived Control

The conceptualization of perception of control assumes that an individual believes that he or she has resources, autonomy, and abilities to affect the environment and outcomes (Rahman et al., 2024). It represents the subjective notion in tourism research that the tourists can control the movement, schedule and experiences they get on the ground despite unpredictability that may arise during the tour like crowding or flights (J. Liu et al., 2025). Based on the control theory and environmental psychology, the perceived control is regarded as one of the fundamental psychological resources, which soften negative responses in high-density environments (Major et al., 2024). Research has always indicated that those who have a feeling of being knowledgeable and able to make decisions declare that they feel more comfortable and more confident (Alafif et al., 2025). Informational support, i.e. clear instructions and proactive updates, in the context of travelling has been associated with a more intensive experience of mastery and autonomy (Hamm et al., 2024). Therefore, the perceived control is usually considered as a key cognitive process involving the process where information systems and service designs could have a significant effect on the emotional and evaluative responses of tourists.

2.3 Stress Reduction

The concept of stress reduction in tourism situations can be described as the alleviation in mental tension, anxiety and emotional exhaustion when a person is travelling (Sayyad, 2025). In conceptualization, it is based on the stress and coping theory, which assumes stress is caused in the absence of sufficient perceived coping resources compared to the perceived demands (Chang et al., 2024). Some of the well-documented stressors in tourism settings include crowded settings, uncertainty, and time pressure (Elshaer et al., 2024). Literature shows that the availability of reliable and timely information may be used as a coping tool because it can make them predict challenges and make appropriate plans (Andrieieva et al., 2024). Cognitive load and perceived risk reduce as soon as the tourists become prepared and guided into lower emotional states. Empirical research on hospitality and smart tourism indicates that technology-based guidance may alleviate the sense of confusion and overload, hence enhancing well-being in general (Zeng et al., 2025). The lowered stress does not only optimize the quality of experience in the moment but also has an effect on post-visit reviews and recollections.

2.4 Temporal Satisfaction

Temporal satisfaction is the judgement that individuals make in the evaluation of their effective and pleasing use of the time through an experience. In theory, it is connected to time perception, time pressure, and congruence of the time expenditure expectations and time expenditures (Hinz et al., 2025). The literature of tourism notes that waiting periods, delays and inappropriate timing of activities can greatly reduce the satisfaction among visitors (Tillet et al., 2025). On the other hand, passengers that feel that they manage their time efficiently and effectively tell of greater pleasure and satisfaction (W. Liu et al., 2025). The studies of service management have indicated that the perceived time efficiency sometimes relates more than the actual time taken since subjective perceptions influence satisfaction results (Pavot, 2024). More positive temporal evaluations have been associated with informational interventions that assist visitors in avoiding queues, scheduling and allocating activities over time (Ngan et al., 2025). Therefore, temporal satisfaction is an aspect of travel quality which is of significant experiential essence.

2.5 Destination Loyalty

The conceptual definition of destination loyalty describes the positive attitudinal and behavioral orientation of a tourist towards a destination in terms of the intentions to return to the destination, recommendations and attachment (Sangkaew & Phucharoen, 2025). It is analyzed extensively in the tourism marketing as one of the main indicators of the long-term destination success (Han et al., 2025). The concept of loyalty is cumulative as a result of being satisfied and having meaningful experiences and not in a transactional form (Ngan et al., 2025). The existing literature indicates that the visitors who feel that destination has high experience quality, low stress, and efficient service provision form stronger positive feelings about the destination. Such attitudes are all forms of advocacy behavior like word-of-mouth promotion and frequent visitation (Kang et al., 2025). It is also highlighted by

scholars that loyalty entails both aspects of cognitive assessment and affective attachment that is destinations need to generate not only functional value but also emotional connections as well (Chua et al., 2025). Crowd-related experiences have become well-known in terms of proper management as part of providing such value to popular destinations.

2.6 Hypothesis Development

2.6.1 Predictive AI Crowd-Management Messaging and Perceived Control

Availability of relevant, actionable, and timely information will result in better perceptions of control by individuals operating within an uncertain situation. Based on the perceived behavioral control theory, perceived control is influenced by the level at which people exhibit a belief that they have resources or information required to undertake behaviors in an effective manner (Xu et al., 2024). The informational support has been revealed to be one of the most essential resources in tourism and service environment which reinforces beliefs of the individuals in their ability to cope with situations and make the best decision (Hamm et al., 2024). Empirical research demonstrates that travelers are more convinced to have greater control over their movements and plans when they are given clear directions on factors like congestion, risks, or timing hence reporting increased perceived control (Alafif et al., 2025). Predictive, AI-based messaging takes this informational support a step further, as it does not only explain the current conditions but also predicts the future level of the crowds as well as proposals beforehand, which only increases the sense of preparedness and self-sufficiency in tourists (Raizada, 2025). This is also consistent with the stress and coping theory which assumes that stress occurs when situational requirements surpass perceived coping resources whereas availability of informational resources encourages problem-oriented coping as well as increased feelings of control (Sayyad, 2025). Based on the empirical evidence of the tourism and mobility studies, real-time and anticipatory information makes people less uncertain and allows them to evaluate the situations as controllable instead of dangerous (W. Liu et al., 2025). Notably, predictive guidance enables tourists to take proactive adjustments, which makes them believe that results to some extent are manageable.

- H1: Predictive AI crowd-management messaging positively influences tourists' perceived control.

2.6.2 Perceived Control and Stress Reduction

Sense of control of people is central in determining the emotional reactions of people to the demanding environments (Macriga et al., 2024). Based on the stress and coping theory, stress occurs when an individual feels that situational demands surpass his or her coping resources, and a sense of control is a psychological resource that helps one to cope more effectively (Rahman et al., 2024). In this belief that people can manage results, make decisions, and have access to the necessary information, people will tend to choose focus

on the problem-oriented coping instead of feeling anxiety or emotional overload (J. Liu et al., 2025). Empirical research on the environmental psychology and tourism has persistently revealed that congested and uncertain spaces increase stress, yet these adverse effects are reduced when the traveler believes he or she is able to control his or her motions and actions (W. Liu et al., 2025). Perceived control eliminates a sense of helplessness and uncertainty, which are part of the antecedents of stress responses. On the same note, the perceived behavioral control theory argues that when people are convinced that they can control the situation and they have the means to do so, they feel more confident and less psychologically strained (Major et al., 2024). Empirical data on travel, leisure, and service studies reveal that perceived control is enhanced by informational support and autonomy enhancing environment and consequently leads to a decrease in stress levels (Hamm et al., 2024). The ones who can adjust their schedules and avoid congestion, and control what they are going through, are likely to rate situations as less threatening and more controllable.

- H2: Perceived control negatively influences tourists' experienced stress.

2.6.3 Stress Reduction and Temporal Satisfaction

Emotional orientation of travelers is a significant factor in deciding how they perceive the time spent on an experience (Sayyad, 2025). Stress level theory is based on stress and coping theory, lower levels of stress mean that situational demands are surmounted due to which an individual is able to devote his or her cognitive and emotional resources to enjoyment instead of having to deal with the stress (Chang et al., 2024). The lesser the psychological tension and anxiety are among the tourists, the higher chances of them viewing their activities as running smoothly and their time spent well. High stress in contrast is related with the perception of rush, delays and time wastage that alters subjective time perception (Elshaer et al., 2024). The theory of time perception in tourism also supports this relationship since it argues that the emotional states affect the way people perceive duration, waiting, and pacing (Andrieieva et al., 2024). Empirical research indicates that stressful tourism experiences, such as congestion, uncertainty, and long queues, tend to result in negative time utilization reviews, and positive and controlled events result in improved time efficiency and satisfaction (Zeng et al., 2025). The decreased stress will enable tourists to stay present-oriented and occupied, thus enhancing their estimations on how well and pleasurably their time is spent (Sayyad, 2025). Previous experiences in the hospitality and leisure settings, also show the same results with the emotionally comfortable visitors reporting their affirmation of satisfaction with the scheduling, pacing, and waiting experiences.

- H3: Stress reduction positively influences tourists' temporal satisfaction.

2.6.4 Temporal Satisfaction and Destination Loyalty

Loyalty is based on the relationship marketing theory that suggests that customers will develop out of gratifying experience in terms of trust, attitudes, and emotional inclinations

towards a service provider or the place of visit (Chua et al., 2025). Temporal satisfaction indicates the judgments by tourists that their time has been spent effectively and in a pleasant way that indicates that the destination is sensitive to the time related expectations of the visitors and that the destination provides value (Han et al., 2025). As soon as travelers believe that time waiting is moderate, activities are timely, and that the schedules set by the travelers correspond to the reality, these people tend to develop positive assessments about the destination (Sangkaew & Phucharoen, 2025). Empirical research in tourism and hospitality shows that time use satisfaction is associated with general satisfaction, which then predetermines revisit intentions and positive word-of-the-mouth (Ngan et al., 2025). Experiences that involve time are salient especially during tourism since vacations have time limits and are often spent planning on the best experiences that can be acquired within a given time (Kang et al., 2025). Favorable temporal assessments consequently get included in the tourists memory format and affect their future behavioral intentions (Strålman, 2025). When the visitors feel as though a destination aids them in making the best use of time, then they are likely to trust the destination and develop positive relational orientation towards the destination.

- H4: Temporal satisfaction positively influences destination loyalty

2.6.5 Serial Mediation Mechanism

The empirical evidence of earlier studies in the area of tourism and consumer psychology proposes that technology-enabled services do not have direct impacts but rather produce effects by a series of cognitive, emotional, and evaluative activities on the outcomes of visitors (Macriga et al., 2024). A combination of perceived behavioral control theory, the stress and coping theory, theory of time perception in tourism and relationship marketing theory gives a consistent explanation to these sequential mechanisms (Chengo et al., 2024). Predictive, artificial intelligence-based crowd-management messaging is an informational and anticipatory tool that increases the perceived control of the tourists by providing them with the impression that they can arrange, modify, and organize their movement in the situation of uncertainty crowd conditions (Alafif et al., 2025). Perceived behavioral control theory is that when a person thinks that he or she has sufficient resources and freedom then the person perceives the situation as more controllable (Menaga et al., 2024). The theory of stress and coping, however, further explains that the advantages of such resources are achieved when they alleviate the strain on the psyche since it is the stress that occurs when the perceived demands surpass the coping ability (Hamm et al., 2024). Therefore, predictive messaging will not decrease stress if it does not enhance perceived control first, and only then, it will act as a coping resource, which will decrease anxiety and tension (Macriga et al., 2024). Emotional states, in turn, determine the way in which tourists do judge their experiences, especially in the context of time usage (Sayyad, 2025). The theory of perception of time in tourism demonstrates that stress negatively influences the perception of subjective time, whereby waits become longer and experiences rush, and vice

versa, when stress is lower, perception of the temporal flow and/or positive judgments of pacing and efficiency are supported (W. Liu et al., 2025). Accordingly, the influence of the perceived control on temporal satisfaction should be mediated by the reduction of stress because only when it effectively decreases emotional strain perceived control will only result in positive time ratings (Chua et al., 2025). Lastly, relationship marketing theory assumes that loyalty is formed out of the overall sum of satisfying experiences that form positive memories and relationship connections (Sayyad, 2025). Though stress reduction enhances immediate well being not every stress reduction is immediately followed by loyalty, a temporal satisfaction offers this bridge by indicating that the destination was mindful of limited time of the tourists and offered them efficient and pleasurable experiences (Hamm et al., 2024). Empirical evidence in tourism and service settings always indicates that domain-specific satisfactions, such as time-related satisfaction, are powerful predictors of revisit and recommendation intention.

Based on the perceived behavioral control theory, stress and coping theory and relationship marketing theory, the reactions of the tourists to technological interventions can be perceived as a series of reactions where informational inputs influence cognitive appraisals to shaping emotions and eventually lead to evaluative and relational outcomes (Sayyad, 2025). Anticipatory and action-oriented information offered by predictive ai crowd-management messaging enhances a sense of control among tourists, making them feel more independent and ready. According to the stress and coping theory, the perceived control is a coping resource which reduces psychological strain hence causing stress reduction (Chang et al., 2024). The subsequent effects of emotional relief on touristic interpretations of the on-site experiences are their time utilization. The studies of time perception in tourism indicate that the low-stress conditions contribute to the creation of more favorable assessment of pace and waiting and increase temporal satisfaction (Elshaer et al., 2024). The relationship marketing theory also explains that the development of loyalty occurs through satisfactory experiences as a cumulative effect of building positive attitudes and relationship. Feeling in control, less stressed, and feeling that their time has been used effectively will positively influence how tourists rate the destination and will increase intentions to remain loyal (Andrieieva et al., 2024). Similar outcomes are empirical studies in smart tourism and services settings that also suggest that the impact of technology-enabled experiences on loyalty is indirect, via cognitive and affective means.

- H5: Predictive AI crowd-management messaging influences destination loyalty through a sequential mediation of perceived control, stress reduction, and temporal satisfaction.

2.7 Theoretical Framework Supporting the Research

The stimulus-organism-response (SOR) theory offers a solid generalized model to understand the influence of external environmental situations to internal states and eventual behavior of individuals. The S-O-R paradigm was initially suggested by (Mehrabian & Russell, 1974) and assumes that the environmental stimuli (S) cause cognitive and affective

responses in the organism (O), which in its turn, result in approach or avoidance responses (R). This paradigm has become widely used in tourism and service research to explain the effect of technological, atmospheric, and informational cues on visitor experiences and loyalty-based behaviors. The predictive AI crowd-management messaging is the stimulus in the current model as it is a technology-based environmental signal, which gives anticipatory and real-time data on the situation of the crowds. This type of messaging lowers the uncertainty and increases the situational awareness, thus triggering internal evaluations. The part of organism is projected in a series of inner states, which are perceived control, stress reduction and temporal satisfaction, and which represent the focus of cognitive appraisal, affective response and evaluative judgment respectively. Using stress and coping lenses that are commonly combined with the S-O-R applications, cognitive evaluations of control determine emotional reactions, whereby the greater perceived control the lower the stress (Ajzen, 1991). The presence of lower stress at the time influences everything to positive evaluative judgment of time use, which causes temporal satisfaction. The earlier researches in the area of tourism confirm the role of cognitive and affective states in mediating the connection amid environmental stimuli and experiential appraisal. Lastly, the response aspect is manifested in the form of destination loyalty which reflects approach behavior like revisit intentions and recommendations. In these regards, the model proceeds in a straightforward S -O -R order in which the predictive aggregate-crowd-management-messaging (stimulus) impacts the internal cognitive/emotional functioning of the tourists (organism) which consequently result to destination loyalty (response), as shown in Figure 1 (conceptual framework). This theoretical perspective provides a logical explanation of the suggested relations and advances the combined format of the research framework:

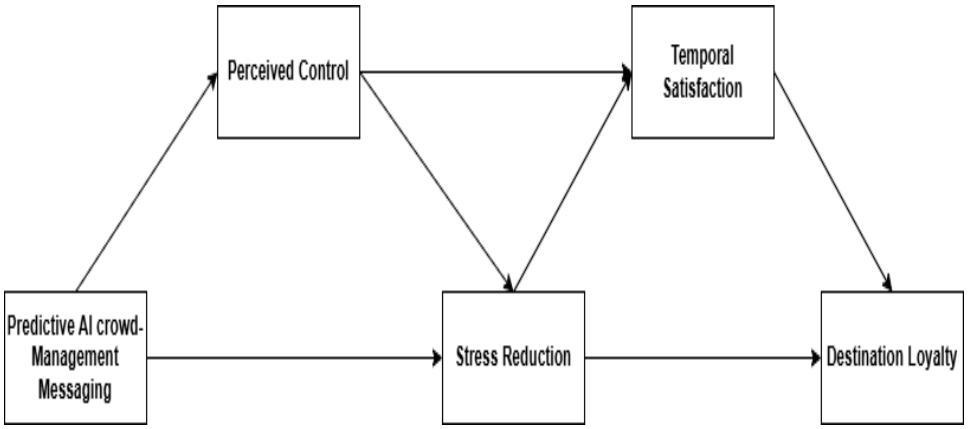

Figure 1: Conceptual Framework

3. Methodology

A quantitative cross sectional research design was used to test the relationships between the proposed variables of perceived control, stress reduction, temporal satisfaction, and destination loyalty, and predictive AI crowd-management messaging. The data were gathered using a structured questionnaire from tourists who were consumers of digital or smart tourism information services in the destinations, in specific, the crowd related information and real-time guidance components. The sampling technique used was purposive to ensure that the respondents have the relevant experience of smart tourism technologies. There was a total of 265 valid responses. The number of samples was deemed acceptable according to the 10 times rule and the statistical power analysis suggested for PLS-SEM analysis (Hair & Alamer, 2022). The minimum sample size is suggested to be at least 10 times the largest number of structural paths that go to any endogenous construct (the 10 times rule). The present model has one less direct antecedent to destination loyalty and the overall model complexity is within acceptable limits for the obtained sample size. Additionally, a sample size of 265 is a bit larger than the minimum recommended by G*power analyses for a medium effect size at a power of 0.80 and at a significant alpha level of 0.05. Thus, the proposed serial mediation model was estimated using the sample size as adequate (Hair & Alamer, 2022).

The scales were all adopted from existing scales that have been published and validated, but have been modified to fit the context of predictive AI for crowd management communication in smart tourism environments. Six items adapted from smart tourism and intelligent information systems literature were used to measure tourists' perception of predictive, personalized and real-time crowd-management information (Gretzel et al., 2015). Tourists' perceived control was captured with six items derived from the perceived behavioral control and consumer control scales measuring their perceived control and influence over their experience in the tourism environment (Ajzen, 1991). The psychological stress and coping literature was used to develop six items for assessing stress reduction: reduction of anxiety, tension, and psychological strain during tourism experiences (Folkman & Lazarus, 1986). The temporal satisfaction was measured with seven items that were adapted from the service management and time-oriented satisfaction literature (Torres & Kline, 2006), which are related with tourists' perceptions of time efficiency, waiting experience, and activity pacing. The six items adapted from existing tourism and marketing measures measuring revisit intentions and positive word-of-mouth recommendations (Zeithaml et al., 1996) were used to measure destination loyalty. Items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Some of the original scales were used in previous research, but they assess long-lasting psychological factors like perceived control, stress, satisfaction and loyalty that are theoretically relevant in a technology independent manner. The items were worded carefully using standard scale adaptation procedures to ensure that the wording was adjusted to reflect current AI applications in the smart tourism world and predictive crowd-

management systems while maintaining the conceptual meaning of the original constructs (Gretzel et al., 2015). This contextual adaptation improves the content validity of the items and their relevance to a new smart destination context.

The analysis of data was carried out using SmartPLS 4 which was carried out in a two-stage PLS-SEM method. The measurement model was subjected to internal consistency reliability, convergent validity tests and discriminant validity tests, first. Cronbach's alpha and composite reliability were used to assess reliability, while average variance extracted (AVE) was used to evaluate convergent validity. Heterotrait–monotrait (HTMT) ratio was used to test the discriminant validity. After establishing satisfactory measurement properties, the structural model was examined by evaluating path coefficients, coefficients of determination (R^2), effect sizes (f^2), and mediation effects. A bootstrapping procedure with 5,000 resamples was used to determine significance for the direct and indirect relationships. Given the recommendations in SmartPLS 4, the model's predictive ability was assessed based on the PLSpredict procedure, instead of the classical blindfolding-based Q^2 technique. To evaluate the model's predictive power out of sample, a 10-fold cross validation procedure was used, and the prediction errors between the PLS-SEM model and a linear benchmark model were compared. The use of PLSpredict allows for more rigorous examination of predictive accuracy and usefulness in current PLS-SEM applications (Hair & Alamer, 2022).

4. Results

As shown in Table 1, the measurement model has a reasonable level of reliability and convergent validity. The values of Cronbach alpha and composite reliability (CR) exceed the suggested value of 0.70 across all constructs, which indicates that items are strongly correlated. In particular, composite reliability scores vary between 0.906 and 0.935, and this indicates that it is highly reliable. The average variance extracted (AVE) values of all constructs are more than 0.50, which proves a sufficient level of convergent validity and reveals that every construct has a greater share of the variance in its indicators, which is more than half. Outer loadings are overwhelmingly above 0.70 with only some a bit below but still useful in exploratory and applied SEM settings. On the whole, these findings prove that the measurement items are reliable and valid to reflect their respective constructs, which can be further analyzed structurally.

Table 1: Reliability and Validity

Constructs	Items	Outer Loading	Cronbach's Alpha	CR	AVE
Destination Loyalty	DL1	0.683	0.874	0.906	0.730
	DL2	0.676			
	DL3	0.839			
	DL4	0.836			
	DL5	0.860			
	DL6	0.805			
Predictive AI Crowd-Management Messaging	PAICMM1	0.832	0.909	0.929	0.700
	PAICMM2	0.807			
	PAICMM3	0.826			
	PAICMM4	0.837			
	PAICMM5	0.831			
	PAICMM6	0.840			
Perceived Control	PC1	0.743	0.898	0.922	0.670
	PC2	0.884			
	PC3	0.886			
	PC4	0.849			
	PC5	0.743			
	PC6	0.775			
Stress Reduction	SR1	0.875	0.910	0.931	0.710
	SR2	0.794			
	SR3	0.866			
	SR4	0.847			
	SR5	0.840			
	SR6	0.762			
Temporal Satisfaction	TS1	0.776	0.919	0.935	0.740
	TS2	0.785			
	TS3	0.827			
	TS4	0.850			
	TS5	0.862			
	TS6	0.780			
	TS7	0.861			

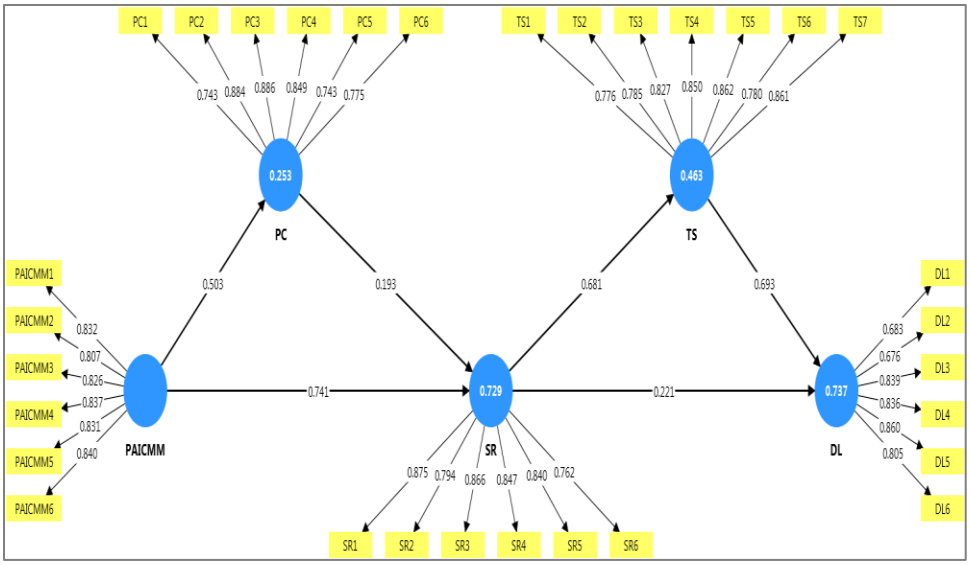

Figure 2: Estimated Model

To ensure the discriminant validity, both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT) were used as per the recent recommendation of PLS-SEM (Hair & Alamer, 2022). According to the Fornell–Larcker criterion, the square root of the AVE for each construct should exceed its correlations with other constructs. Furthermore, the HTMT scores under 0.90 indicate acceptable discriminant validity. The findings showed that all the HTMT values were below the recommended level, which supported that the constructs were empirically separate and experienced different conceptual domains. Since the Fornell–Larcker criterion is less sensitive to detecting discriminant validity issues, HTMT results were given more weight, which is regarded as a more valid indicator in current PLS-SEM research.

Table 2: Discriminant Validity

Fornell–Larcker					
	DL	PAICMM	PC	SR	TS
Destination Loyalty	0.787				
Predictive AI Crowd-Management Messaging	0.689	0.829			
Perceived Control	0.737	0.503	0.816		
Stress Reduction	0.692	0.814	0.566	0.832	
Temporal Satisfaction	0.743	0.711	0.663	0.681	0.821
HTMT					
Destination Loyalty					
Predictive AI Crowd-Management Messaging	0.771				
Perceived Control	0.832	0.553			
Stress Reduction	0.769	0.817	0.625		
Temporal Satisfaction	0.836	0.779	0.719	0.739	-

Prior to evaluating the structural relationships, collinearity among predictor constructs was assessed using the Variance Inflation Factor (VIF). According to (Hair & Alamer, 2022), VIF values below 5.0 indicate that multicollinearity is not a serious concern. As shown in Table 3, all VIF values were below the recommended threshold, confirming the absence of collinearity issues within the structural model.

Table 3: Inner VIF Values

Relationship	**VIF**
PAICMM → PC	1.000
PC → SR	1.339
SR → TS	1.000
TS → DL	1.863

According to Table 4, the model has a high explanatory and predictive power. According to the values of R 2, the model is determined to explain 73.7 percent of variance in destination loyalty, 72.9 percent in stress reduction and 46.3 percent in temporal satisfaction which are said to be substantial to moderate magnitude in behavioral studies. Perceived control is less significant but acceptable with R 2 25.3 which means that predictive AI messaging has an explanation of appreciable portion of its variance. The predictive relevance is valid based on the value of the predictors in Q 2. Values of RMSE and MAE are reasonable, and they indicate acceptable prediction errors. The value of SRMR 0.076 is less than 0.08, which means that it fits the overall model well. All these findings imply that the model is very explanatory and predictive.

Table 4: R-square and Goodness of Fit Indices

	R-square	R-square adjusted	Q^2predict	RMSE	MAE	SRMR
Destination Loyalty	0.737	0.734	0.235	0.889	0.596	0.076
Perceived Control	0.253	0.250	0.698	0.555	0.378	
Stress Reduction	0.729	0.727	0.479	0.729	0.527	
Temporal Satisfaction	0.463	0.461	0.457	0.745	0.545	

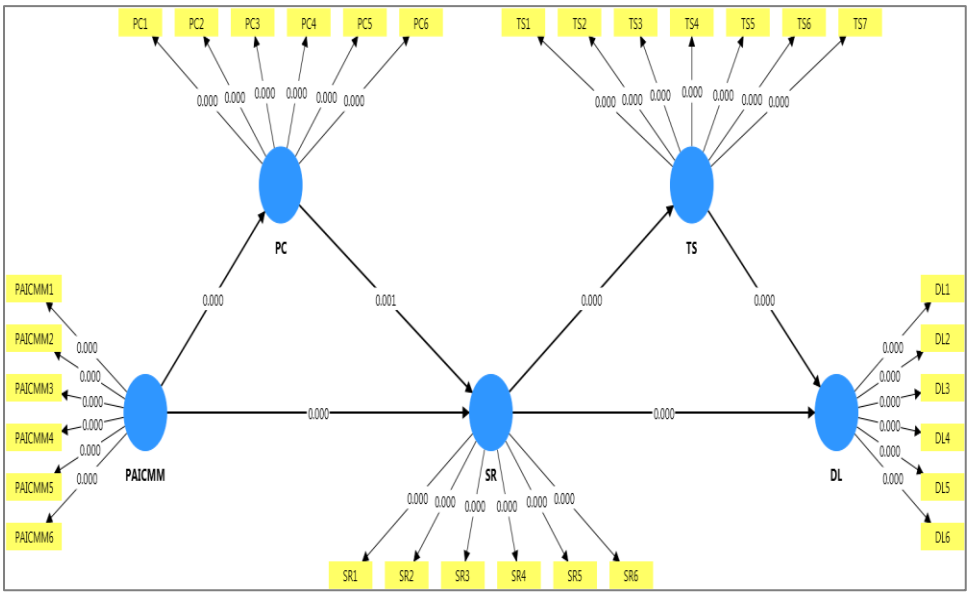

Figure 3: Structural Model for Path Analysis

The results of the structural model assessment are given in Table 5. The results suggest that predictive AI crowd-management messaging is a very significant positively contributing factor to tourists' perceived control ($\beta = 0.503$, $t = 6.331$, $p < 0.001$), thus supporting H1. This finding indicates that predictive and proactive crowd-related information can improve the tourists' capacity to forecast and control the conditions of the destination, thus adding a sense of control to their travel experiences. This result aligns with the latest smart tourism literature, which has been advocating the need for AI-powered information systems to decrease uncertainty and increase tourists' decision-making capabilities by delivering timely and actionable information. In the Stimulus–Organism–Response (S–O–R) model,

predictive AI messaging serves as an environmental stimulus to positively influence tourists' cognitive assessments of destination conditions.

The results also showed that perceived control is a significant factor for reducing stress ($\beta = 0.193$, $t = 3.255$, $p = 0.001$), which supports H2. The finding suggests that tourists who are confident in managing the crowd-related situation have less psychological stress and anxiety. This finding is consistent with past tourism and service-related studies which indicated that perceptions of control serve as a psychological resource for coping with ambiguous and potentially threatening situations. Perceived control, from S–O–R viewpoint, is an internal cognitive state that leads to greater positive emotional responses in the tourism experience. Consistent with H3, stress reduction was shown to have a significant positive effect on temporal satisfaction ($\beta = 0.681$, $t = 14.442$, $p < 0.001$). This significant impact indicates tourists with reduced stress tend to feel they are using their time at the destination efficiently and have a good time. The discovery aligns with previous research suggesting that emotional comfort improves visitors' perceptions of waiting times, pacing of the activities, and overall travel experiences. With the less stressful environment of tourism, it seems that visitors can concentrate on enjoying themselves and getting involved in what they are doing, as opposed to trying to deal with congestion and uncertainty.

The results further indicate that temporal satisfaction has a significant effect on destination loyalty ($\beta = 0.693$, $t = 13.841$, $p < 0.001$), thus supporting H4. This relationship is the most significant direct one in the model, showing the important influence of time-related assessments on tourists' future behavioural intentions. The discovery indicates that when tourists feel their time has been well managed and productive, they have increased intentions to return to the destination, as well as recommending it to others. This finding aligns with destination loyalty studies that have been focused on the importance of memorable and efficient experiences to visitor loyalty and relationship. Finally, the serial mediation hypothesis was supported ($\beta = 0.046$, $t = 2.360$, $p = 0.009$), supporting H5. The indirect effect is significant, confirming that the predictive AI crowd-management messaging has a sequential effect on destination loyalty, as perceived control, perceived reduction of stress and perceived satisfaction with the temporal aspects of the destination. The results obtained here offer robust empirical evidence for the Stimulus – Organism – Response model, in that technological interventions have no direct effect on loyalty, but instead are mediated through a series of cognitive, affective and evaluative responses. In other words, predictive AI messaging can bolster perceived control, thereby lowering stress, and this leads to increased satisfaction with the time and fosters higher destination loyalty. It provides a new contribution to the smart tourism literature by demonstrating the effectiveness of the AI-based crowd management system not only through the technological but also the psychological and overall tourism experience perspective.

Table 5: Path Analysis

Path	β	t-value	p-value
H1: Predictive AI crowd-management messaging positively influences tourists' perceived control.	0.503	6.331	0.000
H2: Perceived control negatively influences tourists' experienced stress.	0.193	3.255	0.001
H3: Stress reduction positively influences tourists' temporal satisfaction.	0.681	14.442	0.000
H4: Temporal satisfaction positively influences destination loyalty.	0.693	13.841	0.000
H5: Predictive AI crowd-management messaging influences destination loyalty through a sequential mediation of perceived control, stress reduction, and temporal satisfaction.	0.046	2.360	0.009

5. Discussion

As AI becomes more prevalent in tourism destinations, it is reshaping the way information related to the crowd is created, disseminated and used by tourists. Unlike traditional information systems which send static messages or real-time updates on crowd conditions, predictive AI crowd-management systems use machine-learning algorithms and historical mobility patterns, sensor data, and real-time analytics to predict crowd state and send proactive recommendations to visitors (Han et al., 2025). This means that visitors are not just reacting to the congestion of their destination, but are also being engaged with by machine-generated predictions of future congestion, waiting times and other ways of travelling to a destination. This study analyzed the effect of this predictive AI crowd management messaging on destination loyalty by considering the cognitive, emotional and evaluative processes based on Stimulus–Organism–Response (S–O–R) model.

The results show that the predictive AI crowd management messaging has a significant impact on tourists' perceived control. This finding implies that a tourist can get more value from information than from predictive information that allows him to make proactive decisions. Providing tourists with information through AI systems, including crowd sizes, potential congestion, and alternative route suggestions, before the issue actually happens, gives them an enhanced sense of readiness and flexibility (Alturki et al., 2026). Predictive AI messaging goes beyond giving visitors the latest information about the crowd; it can help them prevent issues altogether. This finding further contributes to the field of smart tourism in that it shows that tourists are receptive to algorithmically generated forecasts that help with their planning and self-management in dynamic destination environments (Alatawi, 2026). Predictive AI messaging aligns with the S–O–R model and serves as an

environmental stimulus that positively affects tourists' cognitive assessments of their competence in the experience of the destination.

The findings also indicate that a sense of control plays an important role in stress reduction. It is worth noting that the empirical model was based on stress reduction and not perceived stress, so that a positive coefficient suggests that with a higher perceived control, tourists report less stress. This interpretation does away with any uncertainty about the direction of the relationship (Mohanty et al., 2026). The discovery implies that tourists who believe they are able to control the conditions of the destination have positive emotional feelings and less psychological stress. Similar findings have been reported in the tourism and service industry where experiencing a sense of autonomy and control buffers tourists' response to uncertainty and congestion. According to the S–O–R model, perceived control is a cognitive reaction that subsequently affects emotional reactions.

Stress reduction was seen to have a high positive effect on temporal satisfaction. The result suggests that less stress is associated with a more positive evaluation of time spent. This helps the visitors not to get stressed and they can enjoy and engage in the destination activities and things (Chua et al., 2025). Thus, tourists have more positive perceptions of waiting times, activity schedules, and time usage. Overall, the findings highlight the significance of emotional health in the experiential evaluations of tourists and indicate that crowd-management technologies not only contribute to the efficiency of the operation but also contribute to psychological comfort (Hinz et al., 2025).

The findings also show that satisfaction in time is one of the important determinants of destination loyalty and is the most direct among the structural connections. The result demonstrates the significance of time related experiences in a modern tourism situation. One of the key factors in tourists' decisions is whether they are able to make full use of their travel time and have a pleasant experience during that time (Sangkaew & Phucharoen, 2025). Visitors feel that they have not missed out and that their activities have been optimised, they feel they have had a smooth travel and are more likely to have positive attitudes towards the destination and intend to revisit and recommend it to others (Ngan et al., 2025). This result is consistent with previous research on destination loyalty that underscores the effect of experiential quality on destination loyalty.

A second analysis of the impact of predictive AI crowd-management messaging on destination loyalty, known as the serial mediation analysis, also sheds light on how the messaging process works. The findings suggest that the indirect pathway is also significant, indicating that predictive AI messaging plays a role in fostering loyalty by triggering a series of cognitive, emotional, and evaluative reactions that include feeling in control, reducing stress, and experiencing satisfaction (Chengo et al., 2024). But the size of this indirect effect is small ($\beta = 0.046$) but statistically significant. The results indicate that the suggested S-O-R model is relevant, but it is just a small part of many other factors that can affect destination loyalty. The tourist loyalty is multidimensional and can also be influenced by the image of the destination, the service quality, the cultural experiences, the

perceived value, the trust in technology, the attractiveness of the destination, social influences and personal travel motives (Strålman, 2025). Predictive AI crowd-management messaging is not the sole factor that can measure the loyalty but rather an extension of it that can add value to the destinations' outcomes.

Overall, the results validate the S – O – R framework as it has been shown that an AI system for managing the crowd affects tourists by influencing their cognitive, affective, and evaluative stages. By raising awareness about the significance of predictive AI capabilities over simply using technology as a tool for information delivery, the study contributes to the advancement of smart tourism studies. More significantly, the findings indicate that while accuracy of predictions is important, the contribution of AI-supported DMC is also influenced by its capability to improve tourists' sense of control, emotional comfort, and overall travel experience.

5.1 Theoretical and Managerial Implications

This study is part of the smart tourism literature because it adapts the Stimulus–Organism–Response (S–O–R) framework to the smart tourism context of predictive AI-based crowd-management communication. The present research is different from previous research which studied the adoption and intentions of using technology, because it shows that, predictive AI messaging draws the attention of tourists in a cognitive, emotional, and evaluative way: perceived control, reduction of stress, and satisfaction in the short duration. The study results also reveal the difference between predictive AI communication and traditional real-time information systems, emphasizing how predictive AI can influence tourist experiences. While the indirect pathway to destination loyalty was statistically significant, but relatively small, the study offers an important psychological pathway that demonstrates the value of predictive AI communication in destination experiences, and indicates that additional contextual and experiential factors beyond those examined contribute to destination loyalty.

The results offer practical suggestions to destination managers interested in embedding AI-based crowd management systems in smart tourist destinations. The findings reveal the potential value of predictive AI not just as a source of knowledge, but as a tool that can provide proactive advice, allowing tourists to make informed choices about routes, schedules, and avoiding crowds. This predictive communication can benefit tourists' perceived control, ease their psychological strain and foster their overall experience evaluation. But, with the relatively small indirect impact on destination loyalty, destination managers should not only use predictive AI systems as a loyalty-building tool. Rather, AI-powered crowd management solutions should be complemented with larger-scale efforts to improve the quality of services, visitor engagement, destination attractiveness and the visitor experience to ensure sustainable improvement in visitors' satisfaction and their loyalty.

5.2 Limitations and Future Research

Despite its contributions, this study has several limitations that should be considered when interpreting the findings. First, the study looked at tourists' perceptions of predictive AI crowd messaging, and not the actual predictive accuracy of AI algorithms. The results, then, reflect consumer reactions to the AI-generated content rather than its accuracy of the prediction itself. Future studies can combine the system generated data and prediction accuracy evaluations to explore how the success of predictions will affect visitors' experiences. Second, predictive AI systems are based on vast amounts of real-time location and behavioral data. This study, however, did not examine tourists' concerns about privacy, their confidence in AI systems, their understanding of transparency of algorithms, or their willingness to share personal information. These factors could have a strong impact on tourists' perceptions and use of predictive crowd management information and deserve further research. Third, the study considered predictive AI crowd management messaging as a single construct. In reality, the level of personalization, explainability, accuracy and responsiveness that AI-driven communication provides can be significantly different. Future studies can focus on a particular facet of predictive AI systems that could be most relevant to feelings of control, reduction of stress, and destination loyalty. Fourth, tourists can be influenced differently by predictive AI technologies based on their technological readiness, digital literacy, age, traveling experience and knowledge of smart tourism applications. These factors could be explored in future research as moderators to gain deeper insights into the circumstances in which predictive AI messaging works best. Lastly, the study only looked at digital crowd-management communication and not how AI-powered messaging would play a role with other crowd-management methods including physical infrastructure, signage systems, visitor routing and on-site staff. The next research could focus on the combined effect of technological and non-technological interventions on the management of the visitor experience within smart destinations.

5.3 Conclusion

With the growth of smart tourism technologies being implemented by more destinations, predictive AI crowd-management messaging becomes a useful communication tool to help tourists in crowded locations. The results of this research show that predictive AI crowd-management messaging positively impacts tourist's perceived control, stress, and temporal satisfaction, and affects destination loyalty. The results, rather, show that these effects take place in a temporal order, in which predictive information leads to cognitive, emotional, and evaluative responses which then lead to loyalty-related consequences. The study empirically supports the Stimulus–Organism–Response framework by showing that technology-mediated communication influences behavioral response mediated by internal psychological processes. In particular, predictive AI crowd management messaging serves as an external control which boosts perceived control, which in turn lowers stress levels and improves temporal satisfaction, which increases destination loyalty. The results highlight the potential of predictive AI communication systems to augment the current

crowd-management strategies and enhance the guest experience for destination managers. Predictive AI Messaging can complement, not compete with, physical infrastructure and traditional operations as it serves as a valuable supplement that delivers timely, personalized and actionable information to tourists to help them make more informed travel choices. This combination of technological and operational crowd-management methods could give destinations a better chance of improving the well-being of visitors, quality of experience and long-term loyalty.

Research Funding

The authors received no research grant or support for this research study.

Availability of Data

The dataset is available from the corresponding author upon reasonable request.

Declaration of AI Use

AI-assisted tools were used only for language refinement, grammar correction, sentence restructuring, and improving the overall readability of the manuscript during the writing / revision process. No AI tools were used for data collection, statistical analysis, interpretation of results, or development of the study's scientific content.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Alafif, T., Jassas, M., Abdel-Hakim, A. E., Alfattni, G., Althobaiti, H., Ikram, M., Alharbi, A., Alsharif, H., Alshamrani, M., & Alharbi, E. (2025). Toward an integrated intelligent framework for crowd control and management (IICCM). *IEEE Access, 13*, 58559-58575. https://doi.org/10.1109/ACCESS.2025.3555154

Alatawi, M. N. (2026). Deep learning-driven mobile crowd sensing for secure and efficient Hajj pilgrimage management. *International Journal of Mobile Communications, 27*(2), 198-218. https://doi.org/10.1504/IJMC.2026.151581

Alsharif, A., Isa, S. M., & Alqudah, M. N. (2024). Smart tourism, hospitality, and destination: A systematic review and future directions. *Journal of Tourism and Services, 15*(29), 72-110. https://doi.org/10.29036/jots.v15i29.746

Alturki, R., Wedyan, M., & Nasayreh, A. (2026). AI-powered directional anomaly detection in dense Hajj crowds for proactive safety management. *Journal of King Saud*

University: Computer and Information Sciences, *38*(1), Article 102285. https://doi.org/10.1007/s44443-026-00793-5

Andrieieva, O., Byshevets, N., Kashuba, V., Loshytska, T., & Golovanova, N. (2024). The potential of adventure tourism as a means of preventing stress-related states in students during wartime. *Physical Rehabilitation and Recreational Health Technologies*, *9*(5), 418-430. https://doi.org/10.15391/prrht.2024-9(5).08

Chang, W.-Y., Wang, X., Guo, D.-S., Nguyen, L.-H.-P., Tran, N.-H., Yang, S.-J., Lin, H.-Z., Wu, H.-C., & Huang, C.-F. (2024). Explore the effects of forest travel activities on university students' stress affection. *Frontiers in Psychology*, *14*, Article 1240499. https://doi.org/10.3389/fpsyg.2023.1240499

Chengo, M., Bitok, J., & Maingi, S. W. (2024). Crowd management, risk assessment strategies and sports tourism events in Nairobi County, Kenya. *Journal of Hospitality and Tourism Management*, *7*(1), 46-66. https://doi.org/10.53819/81018102t4253

Chua, B.-L., Kim, S., Ling, E. S. W., Xu, Y., Ryu, H. B., & Han, H. (2025). Wellness tourism destination loyalty formation: the role of mental health and eudaimonic well-being. *Journal of Hospitality and Tourism Insights*, *8*(3), 1049-1072. https://doi.org/10.1108/JHTI-06-2024-0551

Elshaer, A. M., Khalifa, G. S. A., Ben Guirat, R., Bulatovic, I., El-Aidie, S. A. M., & Marzouk, A. M. (2024). Managing stress and building resilience in tourism and hospitality entrepreneurship: The power of psychological and social capital. *Journal of Tourism and Services*, *15*(28), 89-115. https://doi.org/10.29036/jots.v15i28.601

Folkman, S., & Lazarus, R. S. (1986). Stress processes and depressive symptomatology. *Journal of Abnormal Psychology*, *95*(2), 107-113. https://doi.org/10.1037/0021-843X.95.2.107

Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: Foundations and developments. *Electronic Markets*, *25*(3), 179-188. https://doi.org/10.1007/s12525-015-0196-8

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), Article 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hamm, J. M., Lachman, M. E., Duggan, K. A., Mogle, J. A., McGrath, R., Parker, K., & Klepacz, L. M. (2025). When and how perceived control buffers against cognitive declines: A moderated mediation analysis. *Psychology and Aging*, *40*(1), 39-53. https://doi.org/10.1037/pag0000841

Han, H., Otoo, F. E., Kim, S., Radic, A., Quan, W., & Lee, S.-M. (2025). Film-induced senior tourism and destination loyalty. *Tourism Recreation Research*, *50*(5), 995-1010. https://doi.org/10.1080/02508281.2024.2362113

16. Hinz, A., Mehnert-Theuerkauf, A., Glaesmer, H., Schroeter, M. L., Tibubos, A. N., Petrowski, K., & Friedrich, M. (2025). Changes in life satisfaction over six years in the general population: A longitudinal study with the Satisfaction With Life Scale (SWLS). *PLOS ONE, 20*(1), Article e0316990. https://doi.org/10.1371/journal.pone.0316990

Kang, S., Gon Kim, W., & Lee, S. (2025). Using nostalgia to increase tourists' destination loyalty in heritage cities: From imagined to productive nostalgia. *International Journal of Urban Sciences, 29*(1), 195-220. https://doi.org/10.1080/12265934.2025.2452511

Li, Y., Hu, C., Huang, C., & Duan, L. (2017). The concept of smart tourism in the context of tourism information services. *Tourism Management, 58*, 293-300. https://doi.org/10.1016/j.tourman.2016.03.014

Liu, J., Ma, E., Zhong, W., & Hu, B. (2025). Going above and beyond for your own sake? An integrated model of hotel employees' OCB, workplace thriving, and perceived control. *International Journal of Hospitality Management, 128*, Article 104169. https://doi.org/10.1016/j.ijhm.2025.104169

Liu, W., Alsalehi, S., Mehdipour, N., Bartocci, E., & Belta, C. (2025). Quantifying the satisfaction of spatio-temporal logic specifications for multi-agent control. *IEEE Transactions on Automatic Control, 70*(8), 5098-5113. https://doi.org/10.1109/TAC.2025.3538747

Macriga, G. A., Bavyatha, S., Abhinidhi, S., & Jagadeesh, N. (2024). Crowd management using AI & ML. In Proceedings of the 2024 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS) (pp. 1-6). *IEEE International Conference*. https://doi.org/10.1109/ICPECTS62210.2024.10780050

Mehrabian, A., & Russell, J. A. (1974). The basic emotional impact of environments. *Perceptual and Motor Skills, 38*(1), 283-301. https://doi.org/10.2466/pms.1974.38.1.283

Mehraliyev, F., Choi, Y., & Köseoglu, M. A. (2019). Progress on smart tourism research. *Journal of Hospitality and Tourism Technology, 10*(4), 522-538. https://doi.org/10.1108/JHTT-08-2018-0076

Menaga, D., Angelin, J. J., & Priyadharshini, V. P. (2024). Sentinel watch: Harnessing AI and ML for proactive crime prediction and crowd management. In Proceedings of the 2024 International Conference on Sustainable Communication Networks and Application (ICSCNA) (pp. 1-6). *IEEE International Conference*. https://doi.org/10.1109/ICSCNA63714.2024.10864034

Mohanty, P., Sharanya, M., & Bharti, S. (2026). A framework for smart innovations in Islamic pilgrimage: Utilizing AI and IoT within the context of halal tourism. In A. Sharma, S. Arora, & H. Pamukçu (Eds.), Halal tourism and artificial intelligence: New approaches

for a new generation (pp. 109-128). Emerald Publishing. https://doi.org/10.1108/978-1-80686-165-120261009

Ngan, H. F. B., Eddy, M. E., & Fong, M. H. (2025). Trust, privacy and smart tourism technologies (STTs): Effects on satisfaction and destination loyalty. *Journal of Vacation Marketing*. First published online October 9, 2025. https://doi.org/10.1177/13567667251383176

Novera, C. N., Ahmed, Z., Kushol, R., Wanke, P., & Azad, M. A. K. (2022). Internet of Things (IoT) in smart tourism: A literature review. *Spanish Journal of Marketing-ESIC, 26*(3), 325-344. https://doi.org/10.1108/SJME-03-2022-0035

Pavot, W. (2023). Temporal Satisfaction with Life Scale (TSWLS). In F. Maggino (Ed.), Encyclopedia of quality of life and well-being research (2nd ed., pp. 7166-7169). Springer. https://doi.org/10.1007/978-3-031-17299-1_2993

Rahman, I., Nanu, L., Bernard, S., & Liu, S. (2024). Does perceived control matter in the early days of COVID-19 in USA? A protection motivation approach examining hospitality and tourism service patronage. *International Journal of Hospitality & Tourism Administration, 25*(3), 638-664. https://doi.org/10.1080/15256480.2022.2142995

Raizada, V. (2025). AI-Based Predictive Analytics of Visitors to Public Places and People Management in India. Impact and Policy Research Institute. https://www.impriindia.com/insights/policy-update/ai-analytics-and-india [accessed on 06-06-2026].

Sangkaew, N., & Phucharoen, C. (2025). Bridging Supply and Demand Perspectives: The Nexus Examination of Destination Attributes, Destination Loyalty, Perceived Competitiveness, Length of Stay, and Tourism Expenditure. *International Journal of Hospitality & Tourism Systems, 18*(3). https://doi.org/10.21863/ijhts/2025.18.3.002

Sayyad, F. Z. (2025). Examining the impact of mindful travel on stress reduction and mental well-being. In A. E. Jimenez Ruiz, V. Rudkouskaya, & N. Landeta Bejarano (Eds.), Promoting sustainability in psychosocial travel techniques (pp. 137-154). IGI Global. https://doi.org/10.4018/979-8-3693-3150-7.ch007

Shin, H., Kim, H., & Kang, J. (2025). Tourist ESG engagement behaviors: Conceptualization, scale development, and nomological network. *Journal of Sustainable Tourism, 33*(12), 2616-2646. https://doi.org/10.1080/09669582.2025.2453680

Strålman, S. (2025). Understanding the emotions of tourists' experience toward national parks: Antecedents of destination loyalty and satisfaction in Serbian national parks. *European Journal of Tourism Research, 40*, Article 4010. https://doi.org/10.54055/ejtr.v40i.3852

Tillet, J., Besset, A., & dit Sandretto, J. A. (2025). Guaranteed satisfaction of a signal temporal logic formula on tubes. *Acta Cybernetica, 27*(2), 315-338. https://doi.org/10.14232/actacyb.315054

Torres, E. N., & Kline, S. (2006). From satisfaction to delight: A model for the hotel industry. *International Journal of Contemporary Hospitality Management, 18*(4), 290-301. https://doi.org/10.1108/09596110610665302

Wu, W., Zhang, Y., & Liu, H. (2025). Analyzing crowd emotional contagion in metro emergencies through the lens of the Weber-Fechner law: Predictions based on computational techniques applied to science. *Applied Sciences, 15*(3), Article 1244. https://doi.org/10.3390/app15031244

Xu, X., Wang, Y., Zhu, Q., & Zhuang, Y. (2024). Time matters: Investigating the asymmetric reflection of online reviews on customer satisfaction and recommendation across temporal lenses. *International Journal of Information Management, 75*, Article 102733. https://doi.org/10.1016/j.ijinfomgt.2023.102733

Yi Wang, Z., Wenyuan, H., Kumari, P., Tian, F., & Zhang, S. (2025). The influence of smart tourism technology on use intention, perceived value, and tourists' net benefits. *Journal of Quality Assurance in Hospitality & Tourism*. Published online: 11 Apr 2025. https://doi.org/10.1080/1528008X.2025.2488428

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing, 60*(2), 31-46. https://doi.org/10.1177/002224299606000203

Zeng, Y., Di, B., Liu, X., He, W., Li, J., Shui, Y., Zhang, B., Chen, H., Zhang, M., & Pan, Q. (2025). Worse or better? Incorporating the time perspective into residents' life satisfaction during temporary housing. *International Journal of Disaster Risk Reduction, 125*, Article 105727. https://doi.org/10.1016/j.ijdrr.2025.105727