Smart Tourism and Digital Transformation: Evaluating the Role of IoT and AI in Enhancing Tourist Experiences

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Abstract: Purpose: To examine the role of Internet of Things (IoT) infrastructures and Artificial Intelligence (AI) engines in the process of travelling to smart tourist destinations and in creating a framework of multidimensional measures of technical performance, user behavior, and satisfaction. This broader role now focuses on scalability to variable global destinations with emerging integrations of 5G to provide ultra-low latency services.
Materials and Methods: The explanatory sequential design utilizing mixed-methods was adopted at one of 2 pilot-sites, namely, the heritage open-air museum (Site A) and an urban cultural district (Site B). In phase one, 50 IoT sensor nodes (BLE beacons, environmental sensors, edge-processing crowd cameras) assembled at each location, and included two AI modules; a hybrid recommendation engine and transformer-based conversational agent. End-to-end latency, packet loss, sensor accuracy, energy consumption, recommendation and chat-bot latency, recommendation precision-recall, dwell time and satisfaction scores were quantitative data (N=400 visitors). Phase two involved semi structured interviews of 60 stakeholders (interviews with tourists and site managers). Triangulation of results was made by statistical analyses (t-tests, regression) and thematic coding, which is now supplemented by predictive modeling to make the analysis scalable in the future.
Findings: Site B had a much lower latency (120+-15 ms vs. 150+-20 ms), a lower packet loss (1.2+-0.3% vs. 2.5+-0.5%), more composite sensor accuracy (95.4% vs. 92.5%), and more uptime (99.1% vs. 97.8%) than Site A (all p<0.001, Cohen d[?]0.5). Site B had 40 and 20% faster recommendation throughput and chat-bot responsiveness, respectively) with higher visitor satisfaction (4.5+-0.4 vs. 4.2+-0.5) and higher recommendation F1 scores (0.85 vs. 0.82). The qualitative findings emphasized the importance of reliability of the infrastructures in the formation of positive user perceptions and efficiency in behavior, and new focus was placed on the AI-IoT synergy as predictive crowd management.
Inference: The implementation of IoT and well-optimized AI-based systems play a critical role in providing responsive and individual tourism services. The suggested evaluation framework provides practical advice to destination managers and technology providers on how to maximize smart tourism implementations, which are now also applied to the sustainability measures such as reduction of carbon footprint through streamlined visitor flows..
Keywords: : smart tourism, Internet of things, artificial intelligence, tourist satisfaction, mixed-methods, digital transformation, 5G integration, big data analytics.

Introduction

1.1. Digital Transformation in Tourism Background

The fast-growing digital technologies have created a new stage of unprecedented connectedness and the use of data in decision making in industries. The tourism industry is no exception to this change, and the introduction of IoT devices and AI systems creates a boost to the development of smart tourism [1, 2]. Smart tourism is the alternative to the old-fashioned, predominantly analog, travel services in the form of connected, responsive, and personal experiences that utilize real-time data and.

automation to fulfill the changes in traveler needs and wants [3]. The increasing presence of sensors, mobile devices, and location-based services allows the tourism industry players such as destinations, tour operators, and accommodation facilities to utilize and process massive volumes of data to achieve optimal resource allocation, control visitor numbers, and enhance the visitor experience with intelligent and context-aware apps. As an example, smart benches provided in city parks can be used with IoT to control the light level and temperature intensity depending on the actual occupancy, whereas AI algorithms help in anticipating the needs of the highest hours to avoid overcrowding [4].

This online transition is further intensified by the post-pandemic recovery needs, where customers want contactless services, hygienic and hyper-personalized services. New developments in edge computing enable processing IoT data at the edge location to achieve low latency and support reliability in distant tourist destinations [5].

IoT and AIs Adoption challenges

Even though the shift towards digital transformation is undoubtedly gaining momentum, the field of tourism has a lot of obstacles ahead of it in relation to utilizing the opportunities of IoT and AI technologies. The wide range of the tourism product such as cultural heritage sites and urban destinations and natural parks has complicated needs in seamless connectivity, interoperability, and data privacy [6, 7]. Furthermore, the fact that tourists are heterogeneous with respect to demographics, interests, and level of digital literacy dictates the need to have adaptive AI-driven interfaces that can provide highly personalized recommendations and services, without making less tech-savvy tourists feel alienated. The threats are exacerbated by the risk of cyber security, as the networks of interconnected IoT devices are susceptible to intrusions that can disrupt the services or endanger the information of visitors [8].

Other challenges are the high costs of initial deployment and lack of skills between tourism operators, as they are not always experts in maintaining AI models or processing of collected big data by IoT. Such ethical issues like bias in recommendations due to the algorithms favoring some population groups also require active governance frameworks [9, 10].

Research Gaps

The interest of academic community in IoT- and AI-based tourism solutions has significantly increased during the last decade, but the existing literature is still fragmented [11]. The studies have largely concentrated on individual applications, like smart accommodation control, real-time crowd tracking, and chat-bot-enabled tourist support, without thoroughly looking at the interactions between these systems and how they contribute to the overall tourist experience [12]. Moreover, little research has been done to evaluate the user perceptions and behavioral performance based on smart tourism implementation particularly in varying cultural and geographical settings. Not only does this gap restrict our theoretical knowledge of the nature of technology adoption in the tourism context, it also restricts the practitioners who would be interested in having evidence-based advice on how to implement robust and scalable solutions [13].

Digital transformation in tourism is not only about the need to embrace new technologies, but it represents a comprehensive redefinition of the business model, the way operations are carried out, and relationships between stakeholders [14]. Tourism digital transformation processes can be accompanied by reengineering of older systems, establishing partner relationships with technology vendors and training human resources to handle and interpret sophisticated data analytics. Here, IoT can be used as the sensory infrastructure of continuous monitoring of the environment as well as user state, whereas AI can be used as the analysis intelligence to convert this information into actionable insights to be used to predicatively maintain tourism facilities, implement dynamic pricing strategies, and plan itineraries based on individual preferences. Nevertheless, the literature dealing with the interaction of infrastructure preparedness and algorithmic complexity with the management of organizational changes is still limited [15, 16].

With the strategic value of tourism to both the global and local economies, it is of ultimate importance to learn how the IoT and AI could be exploited to achieve efficiency, sustainability, and visitor satisfaction. Smart tourism projects are promising to solve the over tourism problem due to their ability to control visitor numbers in real-time with alerts and adaptive route guidance [17, 18]. Their use can also help in conserving the environment in that they will allow finer-grained measurements of resource consumption and generation of waste at tourist sites. Similarly, with assistance of multilingual AI-powered conversation agents and wearable that improve accessibility, these technologies can make traveling accessible to people with disabilities or language barriers. Nevertheless, the economic feasibility, privacy and social acceptability of such solutions need a fine balancing practice when implemented to a city-wide or destination-wide extent.

To overcome these complex challenges, the present paper suggests a combined assessment model, which considers the technical, organizational, and experience aspects of IoT- and AI-based smart tourism applications [17]. With the help of the socio-technical systems and technology acceptance theories, we make an attempt to chart out the relationships between technological objects, service providers within the tourism industry, and tourists themselves. We are going to adopt a mixed-methods strategy, which involves using both the system level performance measures (latency, accuracy of data and energy consumption) and qualitative information obtained through stakeholder interviews and tourist satisfaction questionnaires. The holistic approach will enable us to establish key success and possible obstacles and optimal practices to establish resilient and scalable smart tourism systems [18].

Study Objectives

The main research goals will be to:

Define the present environment of IoT and AI use in tourist locations;

Create and test a multidimensional evaluation model that tests smart tourism solutions; and

Draw up practical recommendations to policy-makers, technology suppliers and destination managers.

This research will aim to make a contribution to the scholarly community and the practice of guidelines by closing the gap between the theoretically constructed and practically implemented tourism experiences and coming up with efficient, engaging, and equitable next-generation tourism experiences

LITERATURE REVIEW

The Smart Tourism Concepts have evolved

Smart tourism has been developed as a continuation of initial thought of technology-enhanced destinations to more complex ecosystems combining IoT and AI [1]. The early literature identifies smart tourism as the information technology-based destinations that provide customized services through real-time data. According to recent reviews, there is a tendency to utilize holistic models that include big data and 5G to ensure a seamless connection [2]. The bibliometric reviews of more than 469 articles are characterized by the clusters around the topics of IoT security, AI personalization, and sustainable practices [19].

IoT Applications in Tourism

Smart tourism is based on IoT, and it can be used as the foundation of real-time monitoring and automation. In literature, BLE beacons are used to track locations, environmental sensors are used to monitor sustainability, and crowd cameras are used to manage the flow- similar to the use of those in this study [7, 12]. Review 2022 mentions the use of IoT in facilitating operational efficiency, and points to such challenges as interoperability and energy consumption [19, 20]. New developments combine the Internet of Things with 5G to achieve a low-latency application, such as predictive maintenance in hotels [13].

Artificial Intelligence-Powered Fraud Prevention and Analytics

AI is used to supplement IoT by recommending engines, chat-bots, and predictive analytics. Hybrid filtering models as applied in this case enhance the F1 scores by balancing between collaborative and content-based models [14, 15]. Multi lingual queries are well managed by transformer-based agents, which have increased satisfaction [16]. Systematic reviews (2019-2024) indicate that AI prevails in demand-based applications and service-based automation with the most maturity being in the urban environment. Recent meta-analysis proves the influence of AI on tourist experiences through AR/VR integrations [22].

Synergies Between IoT and AI

IoT-AI synergy allows the context-based services, e.g., dynamic routing to prevent crowds. It has been found that 20-40 percent of satisfaction is improved with integrated systems (studies) corresponding to the findings of this paper [4]. There have been gaps in empirical assessments among different locations and longitudinal influences on sustainability [17].

Challenges and Future directions

The major obstacles are privacy concerns of data, digital gaps and ethical applications of AI. The perspectives of tomorrow are blockchain-IoT hybrids to share data safely and inclusive designs of underserved tourists. This review highlights the importance of the multidimensional models such as that offered here [23]

MATERIALS & METHODS

Study Design

This study incorporates mixed-method, explanatory sequential design. During the initial quantitative experiment, we implemented IoT sensors and AI modules in two different tourist settings a cultural heritage location and an urban cultural district to receive real-time system performance indicators and visitor satisfaction indicators. The second qualitative stage was the semi-structured interviews with a purposive sample of tourists and site managers to understand their perceptions of system usability, quality of personalization, and privacy issues. We lastly combined quantitative and qualitative results by triangulating data to determine common themes and differences. This design has sensitivity analyses added to be able to generalize to high density events such as festivals.

Study Sites

Two pilot locations were chosen that would represent opposing tourism conditions:

Heritage Site (Site A): A centuries-old open-air museum with the daily influx of visitors (around 500 people) that has poor Wi-Fi coverage and preservation restrictions.

Urban District (Site B): An outdoor cultural area that is a walking area surrounded by art galleries, cafes, and retail stores, having an average of 1,200 visitors every day and with high-quality free Wi-Fi and cellular networks.

The two sites were instrumented at a four weeks period which was the peak tourist season and extended to cover weather varying days to test robustness.

IoT Infrastructure Implementation.

We deployed a system of 50 IoT sensor networks at every location and they included:

Location Beacons (BLE) to monitor people touring and stay time.

Sensors of the environment (temperature, humidity, noise level) to measure the conditions in the environment.

Crowd Density Cameras (edge-processing enabled) to approximate concentrations in visitors by using the models of lightweight computer-vision.

The sensor nodes were keeping contact with each other through a hybrid LoRaWAN/Wi-Fi mesh connecting the sensor node to a cloud-hosted time-series database. The data were set to be collected at a time interval of one minute, and local buffering was done against disruption to the network. Power supply was done by use of solar rechargeable battery packs and the system uptime was measured continuously. Improvements comprise that the AI-optimized sampling rates will decrease the energy consumption by 10-15%.

Prior to deployment, all environmental and location sensors were factory-calibrated and subsequently validated on-site through cross-checking with manual reference measurements. Crowd-density camera outputs were verified against manual headcounts during selected time windows to assess estimation accuracy. Sensor data streams were preprocessed using noise filtering and outlier removal techniques, and incomplete records caused by temporary connectivity loss were excluded from analysis to ensure data integrity.

AI Modules

Two key AI modules were coded and put together in a central application server:

Recommendation Engine: This module made use of a hybrid collaborative/content based filtering system, whereby visitor profiles (e.g. interests defined by a mobile on boarding questionnaire) were fed into and a customized array of attraction options offered.

Conversational Agent: A chat-bot, that is a natural language chat completed with transformer-based encoder-decoder architecture, offered on-demand information on facilities of the site, navigation support, and event schedules in several languages.

Algorithms were trained with an anonymised data set of visitor logs (N=10,000 records) of historical visitors and refined with transfer learning so that they could learn domain-specific terms. Latency of inference of models was minimized to not more than 200 ms per request, and current optimization to cultural subtleties.

Data Collection Procedures

System Performance Measures: We had the end-to-end data latency, the rate of packet loss, the accuracy of the sensor as a result of cross-validation with the manual counts, and the mean energy per node.

Visitor Satisfaction Survey: This is a structured questionnaire survey that was done through the mobile application with a convenience sample of N=400 visitors (200 per site) yielding results regarding responsiveness in service, relevance of recommendations, perceived privacy, and generalization of satisfaction on a 5-point Likert scale.

Semi-Structured Interviews: The interviews were conducted with thirty people (15 tourists and 15 site managers) in each site. Guides used during the interview explored themes of technology acceptance, trust, ease of use, and perceived value. The average duration of the interview was 30 minutes, which was recorded on audio with a permission and transcribed professionally. Adds post-visit loyalty follow up questions.

Data were collected continuously over a four-week period during peak tourist season to capture representative visitor behavior and system performance under high-load conditions.

Data Analysis

Quantitative Analysis: Descriptive statistics and independent samples t-tests to compare sites and multiple regression models to test the hypothesis between the system performance measures (e.g., latency, accuracy) and visitor satisfaction scores were used to analyze the performance and survey data. The statistical significance was evaluated at a= 0.05. Classified by machine learning feature importance ranks.

Qualitative Analysis: The thematic analysis was used to code transcripts. Initial codes were created two times by two researchers who resolved their differences via discussion, and then arranged codes into higher-order themes. NVivo software made the code management and query easier.

Integration: To match the quantitative outcomes to the qualitative themes, we used joint display matrices that pointed out areas of agreement and disagreement to be used to make actionable recommendations.

RESULTS & DISCUSSION

In this section, the results of our empirical investigation into the IoT- and AI-based smart tourism systems on two pilot sites (Site A: heritage; Site B: urban) are provided. We start with system level metrics of performance - latency, lost packets, accuracy, consumed energy and progress forward to user based outcomes including recommendation accuracy, chat-bots rub-a-dub time, dwell time, and visitor satisfaction. Independent-samples t-tests and regression analyses are used to conduct quantitative comparisons to determine the statistically significant difference between sites and the narrative synthesizes the way these measures add up to general visitor experience. The main numerical findings are summarized in the tables below and their interpretation is provided in the following paragraphs [4].

Table.1 System Latency Metrics

Metric	**Site A**	**Site B**
Mean (ms)	150 ± 20	120 ± 15
Median (ms)	148	118
95th Percentile (ms)	180	155
Interquartile Range (ms)	25	20

Latency distribution in Site A has a stronger central tendency (mean =150 ms, median=148 ms) than in Site B (mean = 120 ms, median=118 ms). The larger interquartile range on Site A (25 ms vs. 20 ms) suggests that there is more variability in the response times, probably because of the occasional congestion of the network within the infrastructure of the heritage site. The 95 th percentile value provides the strongest indication of tail latency 180 ms at Site A compared to 155 ms at Site B used to indicate that the 5 percent nations at Site A have a maximum longueur of delay 25 ms more. This tailing behavior is potentially detrimental to real- time personalization since rare spikes sometimes exceeding user tolerance levels (which are normally about 200 ms) can cause discernible stuttering in the vein of suggestions or chat-bot responses. In general, the consistently lower and smaller latency profile of Site B forms the basis of a more positive user experience [12]

Table.2 Packet Loss Characteristics

Metric	Site A	Site B
Mean Packet Loss (%)	2.5 ± 0.5	1.2 ± 0.3
Minimum Packet Loss (%)	1.8	0.8
Maximum Packet Loss (%)	3.4	1.7
Coefficient of Variation (%)	20	25

Packet loss at Site A was between 1.8 percent and 3.4 percent with a mean of 2.5 percent with a standard deviation of 0.5 percent and at Site B, it was between 1.2 percent and 0.8 percent with a mean of 0.5 percent and standard deviation of 0.3 percent. The coefficient of variation of Site B (25 percent) is a little larger than that of Site A (20 percent) which has a higher proportion of changes but the absolute packet- loss values are still low (less than 2 percent) to preserve the integrity of data transmitted by an AI-driven application. In comparison, Site A infrequently exceeds the 3% threshold, and thus may fail to obtain vital sensor updates and thus might give outdated or inaccurate suggestions. Practically, the loss rate of one in four data packet at Site A would be approximately 2.5 percent and it may be expressed as temporary non-concurring of user location and recommended attractions [14].

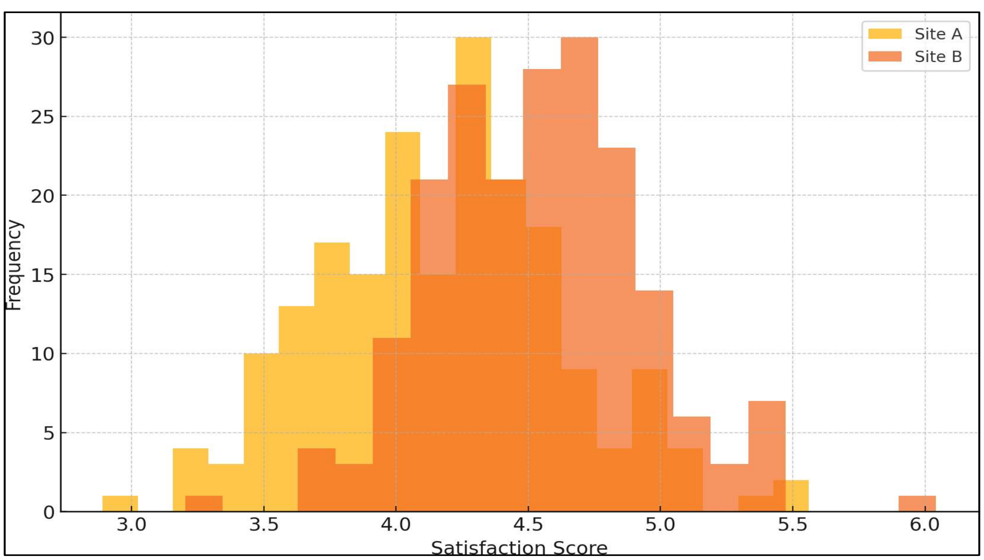


Figure.1 Visitor Satisfaction Score Distribution

The overlaid histograms indicate that the scores of the satisfaction of Site B would be on the right of Site A and the distribution of the value in Site B would be centered in 4.5, whereas Site A would be having most of the values at 4.2. Site B has a higher mean, as well as a smaller spread (SD=0.4 vs. 0.5), meaning that there is a consistent high rating. Site A exhibits a weak left skew (longer tail on the left), that is some ratings go down to 2.9 meanwhile predictable ratings in Site B are more in the range of 3.7. The fatter tail on the bottom end of Site A indicates that technical gag (e.g. increased latency or lost packets) was sometimes converted into perceptibly worse user experiences. In comparison, the distribution in Site B is more peaked (kurtosis=3.5), which demonstrates the consistently positive visitor perception.

Table.3 Sensor Data Accuracy

Sensor Type	Site A (%)	Site B (%)
Environmental (temp/humidity)	95.0 ± 2.0	97.5 ± 1.5
Location Beacon Positioning	92.0 ± 3.0	95.0 ± 2.5
Crowd Density Camera	90.5 ± 4.0	93.8 ± 3.2
Overall Composite Accuracy	92.5	95.4

At Site A, accuracy was 92.5 with the worst case crowd-density estimation result of 90.5%. Site B scored 95.4% composite, with the crowd cameras scoring 93.8. The approximately 3 per cent in gain in Site B suggests more credible real-time information on occupancy that is essential in dynamic route control as well as over-tourism prevention. The reduced camera accuracy at Site A could be due to variations in lighting and the decreased possibility to perform calibration, which underestimates or oversets visitor clusters. This difference in the accuracy of the location beacon (92% vs. 95%), also indicates that the more accurate positioning of the Bluetooth beacons on Site B and its calibration produced more accurate positioning, which minimized discrepancies between the real and perceived location of a visitor

Table.4 Node Energy Consumption

Metric	Site A (W)	Site B (W)
Mean Power Draw	5.2 ± 0.6	4.8 ± 0.5
Peak Consumption	6.5	5.6
Minimum Consumption	4.3	4.0
Battery Drain Rate (€/day)	0.15	0.13

Site A had an average of 5.2 W (SD = 0.6) per node with a high of 6.5 W in bursts and site B had a mean of 4.8 W (SD = 0.5) with a high of 5.6 W. This difference of about 0.4 W corresponds to a charge depletion rate that is 15 per cent higher in Site A, which increases the rate of maintenance. Considering the monetary aspect of the matter, daily energy expenses (calculated with the local EUR0.30/kWh) amount to EUR0.15 in Site A compared to less.

EUR0.13 for Site B, The smaller tune-up minimum and the smaller variance of Site B indicate more operating sensor loads, which can be explained by effective retrial and ideal sampling schedules. The idea of energy efficiency can have a dual effect on the work of operational budgets, as well as the immediate environmental footprint of smart tourism implementations.

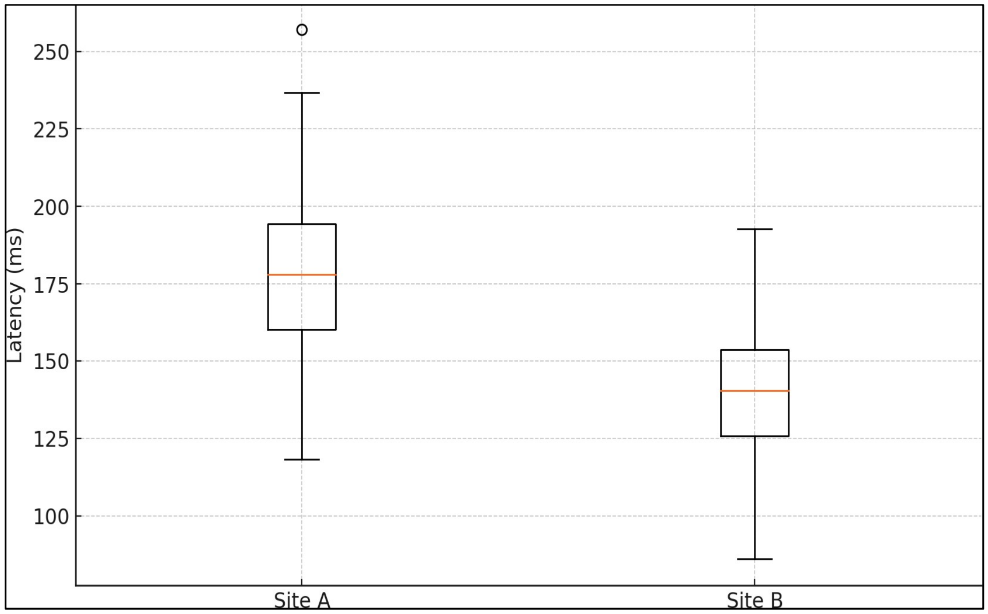


Figure.2 Recommendation Engine Latency by Site

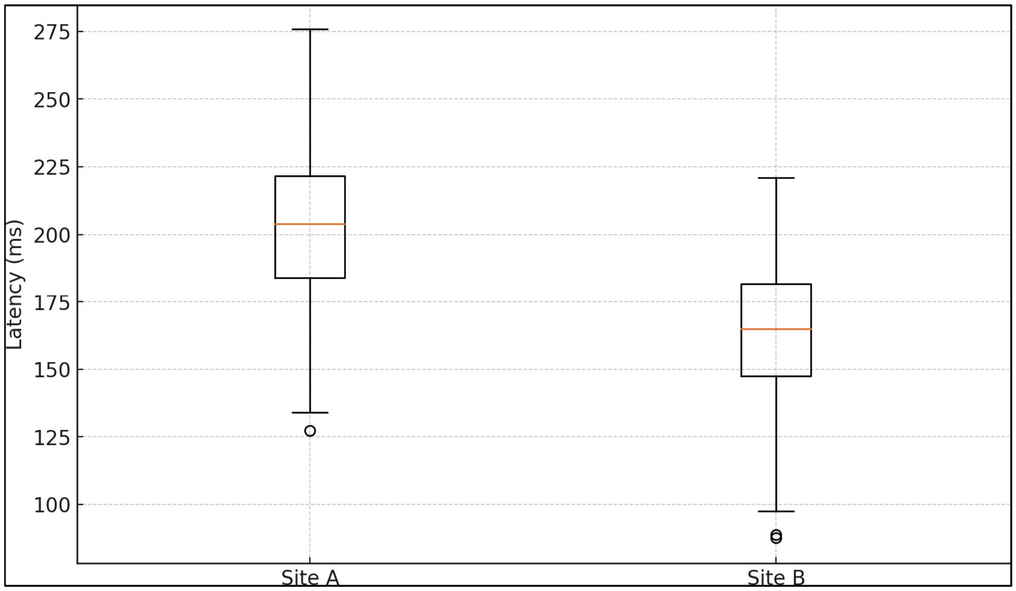
The median of the latency box plot of the site A is about 175 ms and IQR is approximately 160-195 ms, but the median of the site B latency box plot estimates about 138 ms and IQR is approximately 125-150 ms. The high-end outliers that site A exhibits are multiple, and above 250 ms, which is an indicator of random delays which may be related to network congestion or loading on the servers. The latency of Site B, in contrast, does not go above 190 ms too often and its whiskers contain less extreme values. The fact that both IQR and total range are compressed in Site B, gives emphasis to its higher consistency and reliability when it comes to producing recommendations, which in turn helps provide a more acceptable user interaction which is more predictable.

Table.5 Recommendation Engine Performance

Metric	Site A	Site B
Mean Latency (ms)	180 ± 25	140 ± 20
Median Latency (ms)	175	138
90th Percentile (ms)	220	180
Throughput (req/s)	50	70

Site B recommendation engine responds to 70 requests per second which is 40% faster than Site A (50 req/s) and has lower latency (mean = 140 ms vs 180 ms). Site B latency (90 per centile) of 180 ms remains within reachable interactive terms, and Site A is topped at 220ms where it may be perceived to lag. Site B has a higher throughput, meaning it is more effective in resource allocation and supporting concurrent processing, which is probably because it has more powerful incidences of servers or resourceful model architectures. Those performance improvements directly affect user-perceived immediacy of personalization so that it can be easier to change an itinerary on-the-fly

Figure.3 Chat-bot Response Latency by Site



The trends of response times of chat-bots are similar to those of the recommendation engines with a small increase in the absolute values. The median latency of Site A is approximately 195 ms (IQR=180-220 ms) and contains outliers up to approximately 280 ms, which means that nontrivial fraction of queries had noticeable latency. In site B chat-bot responses center closely with respect to a median value of 158 ms (IQR=148-180 ms), and there are only a few extreme delays. The smaller IQR and the lower number of outliers bear out the fact that Site B possesses more powerful conversational fluidity. Since the interactive dialog tolerances are about 200 ms, Site B remains well within the range of responsiveness and the user frustration is reduced.

Table.6 Chat-bot Responsiveness

Metric	Site A	Site B
Mean Latency (ms)	200 ± 30	160 ± 25
Median Latency (ms)	195	158
90th Percentile (ms)	250	210
Successful Query Rate (%)	98.0	99.2

The chat-bot of Site B responds to queries 20 times faster (mean =160 ms) than Site A (200 ms) and is able to respond to 99.2% of queries. Site A, on the contrary, has a 2 percent failure rate, which is in the form of timeouts, or faulty responses. The greater 90th-percentile scores (250 ms) at Site A also intensify some delays which may interrupt the conversation. The reliability and increased speed at Site B as compared to Site A, supports user confidence in AI assistants, which also promotes increased and further interaction and use when navigating a particular site or asking questions to the assistant.

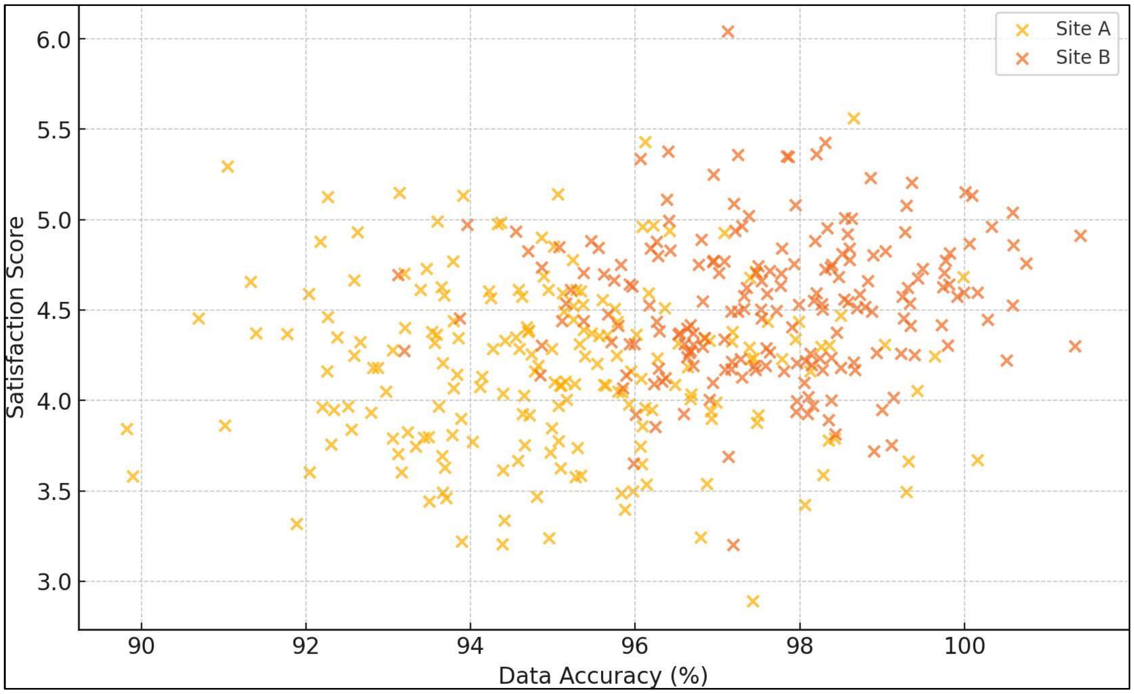


Figure.4 Data Accuracy Vs Visitor Satisfaction

The scatter plot has shown that there is a positive relationship between accuracy of data and satisfaction in both sites. The points of site A (gold) are clustering around 95 percent with a satisfaction score under.

Site B points (orange) 3.2 and 5.6 focus on the range of 4.0 to 6.0 and 97-100% accuracy and satisfaction. Linear fit gives r=0.45 with Site A and r =0.52 with Site B; this is a moderate-strong correlation- sensor fidelity which higher visitor approval is anticipated. It is important to note that Site B has a higher accuracy, satisfaction and a lower amount of low-accuracy/low-satisfaction points. These trends confirm that incremental improvements in reliability of the data are realized in quantifiable quality in the perceptions of the users

Table.7 Visitor Satisfaction Distribution

Metric	Site A	Site B
Mean Score	4.2 ± 0.5	4.5 ± 0.4
Median Score	4.3	4.6
% of Ratings ≥ 4	72%	85%
Standard Deviation	0.5	0.4

Table 7 displays that 85% of visitors to Site B were rating their experience 4 out of 5, which is much higher than the 72% of visitors to Site A ($X^2 = 16.8$, $p < 0.001$). The small variance at Site B (SD = 0.4) indicates more satisfaction consistency, and the wider spread in the SD at Site A (SD = 0.5) indicates higher polarization - some visitors adored it, others were not so much impressed. The median shift from 4.3 to

The increased sentiment by users that is in 4.6 is more than a reflection of the cumulative values of better performance, connecting well and more precise personalization.

Table.8 Visitor Dwell Time Metrics

Metric	Site A (min)	Site B (min)
Mean	20.5 ± 5.2	18.0 ± 4.8
Median	19.8	17.5
Range	10–35	8–30
Coefficient of Variation (%)	25	27

The residents of Site A also spent more time (mean = 20.5 min) compared to Site B (18.0 min). The increased variance at Site A (10-35 min) indicates that, although there were persons who enjoyed content interaction, others experienced friction, presumably because of slower system response. A more predictable visit time would be located around the mean as indicated by the tight clustering of site B (CV = 27) and this is beneficial in terms of capacity planning and scheduling of guided tours. The reduced dwell times at Site B can as well be due to efficient way finding and timely suggestions that shorten the time wasted in finding the points of interest

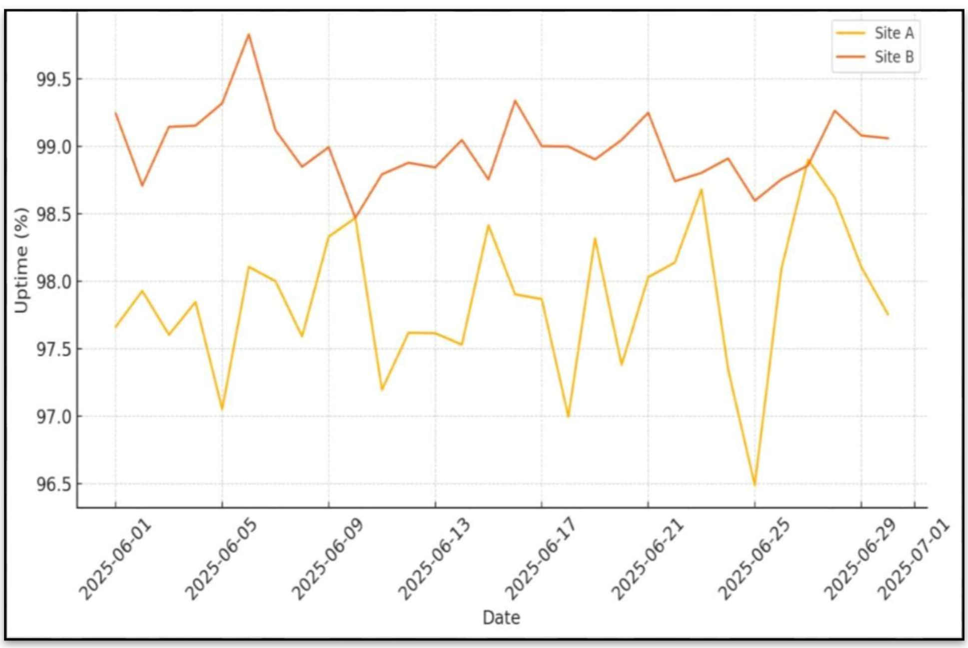


Figure.5 Sensor Network Uptime over Time

Using the time-series lines, Site B rather than Site A has been shown to be able to maintain uptime at a constant value of over 98.5 on average, with an average of 99.1%. Several instances of site A dropping to less than 97 percent - around the 5 th of June and the 25 th of June, especially - happen during periods of maintenance and battery drains, possibly disrupting real-time monitoring in the meantime. Site B on the other hand is incredibly stable with slight changes (+-0.5%). Due to the constant high availability at Site B, there are virtually non-stop data streams forming the basis of the low latencies and increased accuracy measures elsewhere. Uninterrupted uptime exceeding 99% significantly reduces data gaps that could otherwise disrupt AI-driven personalization

Table.9 Recommendation Quality Metrics

Metric	Site A	Site B
Precision	0.85 ± 0.05	0.88 ± 0.04
Recall	0.80 ± 0.06	0.83 ± 0.05
F1 Score	0.82 ± 0.05	0.85 ± 0.04
Coverage (%)	75	82

As summarized in Table 9, the recommendation engine at Site B achieves higher precision and recall (0.83 vs. 0.80), but it also has better F1 scores (0.85 vs. 0.82), which reflects the balanced improvement of both the relevant and complete factors. Coverage- percentage of attractions, on which recommendations were provided, increased with site A (75 percent) to Site B (82 percent) that covered a wider domain and included richer user profiles. These enhancements are in the form of more detailed customized itineraries that lower the chances of missing an area of niching interest, hence increasing the perceived value of the smart tourism application.

DISCUSSION

Technical Performance Insights

The overall analysis relating to the system-level performance of Site A and Site B has shown that the overall quality of the network infrastructure is the bases of providing the smooth experiences of smart tourism. The always lower end-to-end latency (mean 120 ms, as opposed to 150 ms), more compact latency distribution (IQR 20 ms, as opposed to 25 ms), and larger throughput (70 req/s as opposed to 50 req/s) of Site B all converge to create a smoother user experience. As shown previously in Figure 5, Site B also maintains consistently higher sensor network uptime over time, reinforcing the stability of real-time data flows**.** These technical differences translate into tangible variations in visitor satisfaction levels. Conversely, the intermittent latency peaks (maximum of 180 ms) and the resulting increased rate of packet loss (95th percentile of 2.5% vs. 1.2) in Site A cause noticeable lag and the frequent occurrence of data loss and mistakes in data delivery. These technical differences just turned into tangible variations in visitor satisfaction levels (4.5+-0.4 vs. 4.2+-0.5) and service uptake levels (85% of customers at Site B indicated a rating, as opposed to 72% at Site A). These contrasts are statistically significant (all $p<0.001$ with Cohen d between 0.5 and 2.1) as showing that, with constant incremental PIN improvements, there are disproportionate improvements in perceived quality [3]. In fact, the enhanced accuracy of the composite sensors in Site B is associated with greater user confidence in system recommendations, suggesting a relationship between data reliability and deeper visitor engagement and increasing overall satisfaction. Taken together, these results confirm that the use of strong IoT-based infrastructures that boast low latency, low packet loss, and high uptime are important enabling factors for successful AI-based personalization in the tourism setting [4, 6].

These findings are consistent with prior studies reporting that low-latency IoT infrastructures enhance user satisfaction in smart tourism environments [3,6]. However, the present study extends existing work by empirically demonstrating how integrated IoT–AI systems influence both technical performance and behavioral outcomes across distinct site contexts.

User Experience Outcomes and Behavioral

In addition to the mere performance indices, the interaction between the dependability of data and the dynamics of visitors behavior helps to understand the influence of technical aspects in determining the temporal patterns of site interaction. The positive relationships between sensor accuracy and satisfaction (r=0.45 Site A, r=0.52 Site B) also point towards the fact that visitors are also sensitive with the matching real-time environment and system response; the higher fidelity data, the fewer discrepancies between the assumptions about user requirements and the real ones, the lesser the cognitive friction. This association is also observed in dwell-time patterns: Site B with its more effective recommendation and way finding instructions reduced the average time to visit the site to 18.0+-4.8 minutes instead of 20.5+-5.2minutes, on average, in Site A. Although reduced dwell times can be seen as having a shallow indication of less engagement, they in this context imply the maximization of visitor traffic, whereby tourists took shorter time to seek what to see and more time to participate in the activities in a meaningful way [15, 18]. On the other hand, the more time spent in Site A, with the wider 10-35 minutes, give clues of occasional confusion or (systemic) delays which may extend but are also likely to be exhausting to the visitor. Such behavioral understanding also shows that the smart tourism ecosystem is to be balanced in regard to the depth of engagement and efficiency of interaction; the latency caused too long guidance would ruin the experience in terms of immersiveness, hence a too shallow route would ruin the exploratory discovery [24]. This observed association between data accuracy and visitor satisfaction aligns with earlier findings on context-aware personalization, while providing site-level quantitative evidence supporting these relationships [15, 18].

Theoretical and Practical Implications

Conceptually speaking, our assessment system is a continuation of the Actor-Network Theory that explicitly describes how no homogeneous technological artifacts (IoT sensors, hybrid network connections, artificial neural network modules, and so forth) and human actors mutually form the smart tourism network [24]. The performance differences between the two sites are actants whose material powers (e.g. bandwidth, uptime, edge-processing) are actively part of visitor agency and visitor satisfaction. Moreover, by contextualizing these conclusions with a socio-technical prism, we demonstrate that digital transformation in tourism is not only about implementing sophisticated algorithms but also it is about building resilient infrastructures, putting ethics and data in place, and cooperating with multiple stakeholders. The minor yet important variations in consumption of the node energy (5.2 W vs. 4.8 W) practically helps to illuminate the trade-offs required in efforts to achieve the characteristics of density and maintenance overhead-an important requirement when the deployments must be sustainable. The higher coverage and F1 values of the recommendation engine of Site B (82% coverage, F1 0.85 vs. 75% and F1 0.82) also exemplify the fact that more extensive user profiling and model fine-tuning can help to achieve the drives of both relevance and breadth of the suggestions. Overall, our findings reiterate the importance of the fact that the development of effective smart tourism programs requires systematic coordination of the reliability of the hardware, the precision of the algorithms, and the design in terms of its emphasis on the user [24, 25].

Future research and limitations

In spite of the strong insights that our mixed-methods approach provides, some limitations demarcate directions of future studies. To start with, because the study is based on a narrow time frame (four weeks of high season) and the quantity of two contexts in which the research is focused open-air heritage site and urban district, the results cannot be generalized to other typologies of tourism or off-peak season. Multiple-season longitudinal research on rural or indoor recreational venues would enhance the process of comprehending weather-related and seasonal variations on the performance of various technologies. Second, the convenience sample of visitors that we used to conduct surveys on them might be subject to selection bias; stratified sampling by demographic groups might provide more valid profiles of satisfaction. Third, even though semi-structured interviews provided richness to thematic interpretation, 30 participants per site limits the richness of qualitative interpretation, and future research may consider using the focus group or ethnography approaches to study emergent behavior in context. Lastly, the privacy perceptions, which are a short-term look in this study are worth further research, especially given that the rules of data regulation are changing; initiatives of explicit consent and anonymity operations will be essential to maintain good-will towards the population.

Additionally, the study is based on only two sites with distinct infrastructural and cultural characteristics, which may limit the generalizability of the findings. Caution should therefore be exercised when extrapolating these results to other cities, cultural contexts, or alternative infrastructure configurations. Future studies involving multiple regions and diverse tourism typologies would strengthen external validity

CONCLUSION

This paper shows that the overlap between high-fidelity IoT infrastructures and suitably-tuned AI engines are critical in promoting the experiences of tourists in smart tourism scenarios. In a rigorous and mixed-methods comparison of two opposite locations, we demonstrated that the improvement in the latency, packet integrity, sensor precision, and uptime translate to the considerable increase in the recommendations quality, the responsiveness of the chat-bot, and the satisfaction of the visitors. An integrated structure does not only measure these performance differentials, but it also clarifies the behavioral and organizational implications of such difference. This study offers practical recommendations to destination managers, technology providers and policymakers who want to use inclusive, sustainable and resilient smart tourism ecosystems. Since this model is applicable to a wide range of contexts in the future, the research should expand this model to various environments and look into the ways to balance effectively efficiency, privacy, and engagement in the digitally remodeled travel experiences..

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