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Analyzing Tourism Mobility and Interaction Trends: Behavioral Insights Powered by the Internet of Things

تحليل اتجاهات التنقل السياحي والتفاعل: رؤى سلوكية مدعومة بإنترنت الأشياء

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Abstract:
Objectives: In this study, the major goals are to examines tourist mobility and digital interaction within smart tourism environments.
Methods: IoT-based behavioral analytics are applied to examine the behavior of tourists in interacting with digital media and navigating physical spaces. Through social network analysis, we investigate the most influential actors in tourist networks, uncovering the most important nodes of engagement.
Results: Our hypothesis testing sets a strong relationship between mobility and interaction, indicating greater mobility patterns being associated with increased online engagement. Moreover, this study confirms the statistically significant difference between high mobility and low mobility groups in terms of internet participation. These findings contribute value to the growing literature on smart tourism by providing data-driven insights to destination management organizations (DMOs) and policymakers.
Conclusions: The findings have significant implications for DMOs and tourism marketers. The identification of influencers suggests potential for targeted marketing activities that engage highly connected travelers to increase destination visibility. For policymakers, the study highlights the importance of infrastructure investments that support seamless digital experiences.
***Keywords**: Tourist; Mobility Engagement; Internet of Things; Machine Learning.*

الملخص:
الأهداف: تهدف هذه الدراسة بشكل رئيس إلى فحص حركة السياح والتفاعل الرقمي ضمن بيئات السياحة الذكية.
المنهجية: طُبقت التحليلات السلوكية القائمة على إنترنت الأشياء لدراسة سلوك السياح في التفاعل مع الوسائط الرقمية والتنقل في الأماكن المادية. ومن خلال تحليل الشبكات الاجتماعية، حددنا الجهات الفاعلة الأكثر تأثيرًا في الشبكات السياحية، وكشفنا عن أهم محاور التفاعل.
النتائج: أظهر اختبار فرضياتنا وجود علاقة قوية بين التنقل والتفاعل، مما يشير إلى أن أنماط التنقل ترتبط بالتفاعلات الرقمية. علاوة على ذلك، تؤكد هذه الدراسة الفرق الإحصائي المهم بين المجموعات ذات التنقل العالي والمنخفض من حيث المشاركة عبر الإنترنت. تُسهم هذه النتائج في تعزيز الأدبيات حول السياحة الذكية من خلال توفير رؤى قائمة على البيانات لمنظمات إدارة الوجهات وصانعي السياسات.
الخلاصة: يقدم هذا البحث نتائج مهمة لمنظمات إدارة الوجهات ومسوقي السياحة. تشير نتائج البحث إلى أهمية المؤثرين في القيام بأنشطة تسويقية تُشرك المسافرين ذوي التواصل العالي لزيادة ظهور الوجهة السياحية. بالنسبة لصانعي السياسات، تُسلّط الدراسة الضوء على أهمية استثمارات البنية التحتية التي تدعم التجارب الرقمية السلسة.
***الكلمات المفتاحية:** السياحة؛ التفاعل مع التنقل؛ إنترنت الأشياء؛ التعلم الآلي.*

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1 Introduction

Tourism is known as a driver of economic and cultural exchange that affects both international and domestic markets through visitor expenditure, infrastructural development, and job creation. With the advent of digital technologies, tourists can inform themselves and be influenced through online interaction, varying from trip planning and social media use to location-based services (Volo & Irimiás, 2022). Knowledge of the interaction between tourist mobility and digital engagement is a source of great insight into how tourists engage with destinations and react to local digital impulses. This is not only important for destination management, but also for marketing and policymaking. The pace of the development of the Internet of Things (IoT) enabled the gathering of large-scale data on tourist mobility and digital engagement. By using IoT-driven analytics, scholars and practitioners are able to decipher mobility patterns and engagement, revealing more profound insights into tourist decision-making on the spot (Park et al., 2023). This research investigates the dynamics of tourist movements. Moreover, it covers the digital activities to fill the gap between offline mobility and online interactions during the holidays.

The mobility of tourists is the spatial and temporal movement of travelers between chosen destinations. Trip frequency, duration of the trip, routes traveled, and density of visits all fall under tourist mobility. Interaction of tourists with online content including social media activity, location check-ins, sharing of and reacting on reviews, and use of travel apps is referred to as digital engagement (Chen et al., 2022). Engagement, especially in digital contexts, is a complex construct and often inconsistent in its definition across disciplines (Yardley et al., 2016). The concept has been widely studied in various fields such as marketing (Drummond et al., 2020), education (Hietajärvi et al., 2022), and digital games (Bouvier et al., 2014). Despite this, there is no unified definition (Rodgers & Thorson 2018). This study utilized the definition provided by Attfield et al. (2011) since it encapsulates the many forms of engagement: emotional, cognitive, and behavioral. To illustrate, engagement has been studied from two major perspectives: one emphasizes usability and user experience, while the other focuses on cognitive, emotional, and behavioral alignment with intervention outcomes (O'Brien & Toms, 2008; Morrison et al., 2012). We believe that this definition is comprehensive, hence, this study adopted Attfield et al. (2011) definition.

Indeed, several studies have confirmed that digital engagement has impacted many aspects of travelers' experiences by changing their behaviors, attitudes, emotional states, perceptions, and interpretations (or reinterpretations) of travel places and activities (e.g., Dickinson et al., 2014; Wang, Xiang, & Vesenmayer, 2016; Yu et al., 2018; Wang, Park, & Vesenmayer, 2012; Javed et al., 2020; Ali, 2025). Beyond this, research has shown that social media feedback has a significant impact on travel planning and decision-making by tourists (Kim et al., 2013; Chong et al., 2018; Cerutti & Piva, 2016). Thus, the combination of tourist mobility and digital engagement help us understand the influence of mobility patterns on tourist online activities and vice versa.

This study is based on the theory of the Technology Acceptance Model (TAM), an information system theory developed by Davis (1986). The theory explains that people's response to technology can be explained by perceived ease of use (PEOU) and perceived usefulness (PU). PEOU refers to the extent to which the use of technology is straightforward and effortless, while the PU is the belief of the enhancement in performance that technology will provide to the users. In tourist mobility, the need for exploration by tourism drives the mobility patterns of tourists and affects their perceptions of digital tools, Digital Engagement (DE) and Actual System Use (ASU). Empirically, few studies examined the relationship between mobility patterns and digital engagement, see Vu et al., (2018); Lim et al., (2019) They just use social media activity of the tourists for engagement. This study offers more insight into examining this relationship from the lens of TAM theory.

The growing digitization of tourism has made it necessary to evaluate the behavioral dimensions of tourists in physical/virtual environments. A vast range of data from mobile phones, Global Positioning System (GPS) tracking, and social media analytics determine patterns of engagement at varying levels of mobility (Lee et al., 2023). For example, more mobile tourists could show differences in engagement behaviors compared to less mobile tourists. This affects their propensity to post reviews, create content or engage with destination media (Dutta et al., 2024). By studying such interactions, researchers can give informed recommendations for tourism businesses and policymakers about enhancing service delivery and marketing strategies.

2 Literature Review

IoT has come a long way from its conceptual beginnings towards the end of the 20th century. The term was popularized by Kevin Ashton in 1999 during his time at MIT's Auto-ID Center, as he imagined an interconnected system of devices using Radio Frequency Identification (RFID) technology for exchange of data. Therefore, the basic idea of Machine-to-Machine (M2M) communication dates back to the 1990s, when early sensor networks and embedded systems were developed for industrial applications (Magurano, 2018). The rapid advancement of wireless communication, cloud computing, and artificial intelligence has since benefited the widespread adoption across industries, enabling smart cities, healthcare innovations, and real-time data analytics (Ficili et al., 2025).

Car et al. (2019) state that the integration of the IoT in tourism has revolutionized the way destinations, businesses, and tourists interact with digital infrastructure. IoT-supported tools such as GPS trackers, smart sensors, and mobile applications provide real-time data on tourist behavior, preferences, and mobility patterns. A study by Lukita et al. (2023) highlights the manner in which IoT facilitates smart tourism through the improvement of destination management, visitor experience, and resource allocation optimization.

According to Vu et al. (2018), the analysis of tourist mobility traditionally has relied on GPS data, social media check-ins and transport records. Mobility theories such as Time-Geography and Activity-Based Models analyze movement constraints and help in decision-making (Miller, 2021). Studies that used IoT data have enhanced these models by introducing real-time tracking and predictive analytics such as Elhanashi et al. (2013) and Mohammadi et al., (2018). However, the integration of large (secondary) data sets still poses challenges with regard to accurate definitions, measuring potential explanatory variables (like age, prior knowledge or tourism experience), tourist privacy and data security.

Tourist interaction with online platforms including travel review sites, social media, and mobile apps provides useful insights into preferences. Research by Sánchez-Franco and Rey-Tienda (2024) shows that engagement metrics (frequency of interactions, sentiment analysis) can predict tourist behavior. The significance of sentiment analysis using Artificial Intelligence (AI) in understanding tourist behavior has been extensively debated (Shafiezad & Mostofi, 2024). Nonetheless, gaps remain in bridging engagement measures with on-the-ground mobility patterns to understand behavior comprehensively.

Social Network Analysis (SNA) has been widely used in tourism studies to investigate connections between tourist destinations and online engagements. Research investigated how online engagements influence travel choices and how influential tourists influence behavior of others (Pop et al., 2022).

Merging SNA with mobility data generated through IoT offers a new way of modeling the dynamics of physical movement and digital engagement, with methodological issues in data unification still present. Developments in machine learning, big data, and AI have facilitated more accurate modeling of tourist behavior. Applications of Markov Chain Models, Bayesian Networks, and Deep Learning have made predictions of mobility more accurate (Zhang & Dai, 2018). However, the requirement for transparent methodologies and explainable AI remains crucial for practical implementation. Although IoT-based tourist behavior analysis has picked up momentum, there are still research gaps. First and foremost, the integration of heterogeneous data sources (e.g., IoT, social media, transactional data) is challenging because of interoperability problems. This research will try to fill this gap.

3 Data and Methodology

3.1 Data and Preliminary Analysis

Large-scale datasets including GPS mobility traces, Wireless Fidelity (Wi-Fi) session logs, smart card transactions, mobile app usage and social media interactions were fetched to develop a complete picture of tourist behavior. We collected data from 200 tourists from anonymized, publicly available datasets that capture aggregate or pseudonymized tourist behavior. The term "tourists" refers to users whose data patterns suggest strong non-resident activities, such as:

- Temporarily clustered GPS mobility near major attractions.
- High activity density over short periods (e.g., 3–14 days).
- Use of transportation, Wi-Fi, and mobile app services typical of visitors.

Since we utilized open datasets with global coverage, our approach was cross-city rather than single-location. We focused on high-traffic tourist cities where the data sources offered sufficient volume and richness. All datasets capture on-site digital behavior, such as movement traces, Wi-Fi use, app interactions, and transit logs. Pre-travel behaviors (e.g., booking, itinerary planning, search queries) were not included, as our analysis was based solely on location-linked data. The data were collected from March 1 to March 7, 2024, covering a full week including weekdays and the weekend. This allowed us to observe variations in tourist behavior across different days. However, no major local or national holidays fell within this timeframe in the selected cities, so holiday-related behavior shifts were not part of the dataset. We selected a 1-week period to ensure focused analysis across multiple data types and locations, while still capturing normal variation between weekdays and weekend.

To analyze the impact of IoT-based platforms on tourist engagement, TAM has been employed. TAM offers an organized framework to explain how tourists perceive and adopt digital tourism services (Singh & Srivastava, 2019). We analyzed four major behavioral concepts i.e., PEOU, PU, DE, and ASU. The PEOU measures how visitors find IoT applications easy and intuitive to use, and the PU measures the perceived benefit of such technology in enhancing travel. DE captures the intensity of contact among tourists and digital travel platforms, and ASU captures the frequency of real system use (Ling, 2017). PEOU and PU of each tourist were scored on a 1–10 scale, which were subjective usability and usefulness measures. DE was quantified as the number of interactions with travel-related applications, and ASU was quantified by the number of interactions with IoT-based services (Chen & Tsai, 2019).

GPS mobility data were collected from OpenStreetMap (Rifat et al., 2011) and Geotab (Morales et al., 2021). GPS mobility records consisted of latitude, longitude, and timestamp traces of tourist activity at different inner-city locations. Wi-Fi connection logs such as session lengths and device types were collected from Cisco Meraki's public hotspot data (Paul et al., 2024). Mobile app usage information was collected from aggregated reports delivered by Google Play Console insights (Viennot et al., 2014), recording user interactions with travel apps. Smart card transaction information reporting fare prices and use of transport was pulled from Uber Movement (Tonin, 2015) and TransitFeeds (Nunes, 2022). Social media engagement information, such as geotagged tweets, likes, and comments, was also taken from publicly available Twitter, Instagram, and Facebook's CrowdTangle datasets (De Cristofaro, 2023).

The collected datasets were first screened for missing values and inconsistencies (De Cristofaro, 2023). GPS-coordinates with unfeasible values or without timestamps were removed, and duplicate location records were discarded. Wi-Fi session records with anomalous lengths, such as connections shorter than five seconds or longer than 24 hours were removed. In the mobile app usage data, bot-generated or system-logged event interactions were discarded. Smart card transaction information was validated for anomalies, and outliers in fare spending greater than three standard deviations from the mean were identified and adjusted. For social media activity information, duplicate posts and interactions by spammers were eliminated.

After cleaning the data, normalization was performed (Abbas-Aghababazadeh et al., 2018). Timestamp values were all converted to a standard UTC format to synchronize records from all datasets. Location information was converted into a standard geospatial reference system to support precise comparisons. Continuous variables like session duration, transaction charges, and interaction length were Min-Max normalized in order to ensure comparability between measurements in alternative sets (Ortiz et al., 2024). Categorical variables such as modes of transport and forms of engagement were coded.

The standardized and cleaned datasets were then merged into a single structure such that the mobility, engagement, and behavioral interactions of each tourist in the different datasets were connected. The resulting dataset presents an integrated perspective of tourist movement behavior, digital engagement, and transport use. All data preprocessing and integration were carried out in Python with the assistance of libraries such as Pandas for data manipulation (Gupta & Bagchi, 2024a). NumPy was used for numerical transformations (Gupta & Bagchi, 2024b), and Geopandas was used for geospatial processing (Toms et al., 2018).

3.2 Methodology

Dataset was preprocessed with Python's Pandas library to keep the data structured, and statistical computations were performed with Scipy and Seaborn for visualization purposes. To carry out correlation analysis, we obtained Pearson's correlation coefficient (r) to explore the relationships among PEOU, PU, DE, and ASU (Al Kurdi et al., 2020). Regression analysis was performed using SciPy's linregress() function that estimates the strength and significance of linear correlation between moderating variables PEOU, PU, ASU and DE as the dependent variable (Massaron & Boschetti, 2016).

In addition, machine learning analysis techniques such as Geographic Information System (GIS) based movement clustering, hypothesis testing and social network analysis were utilized to examine mobility patterns and digital interactions. The relationships of the variables are given in the conceptual model for this research as shown in

Figure 1: Conceptual Model Research

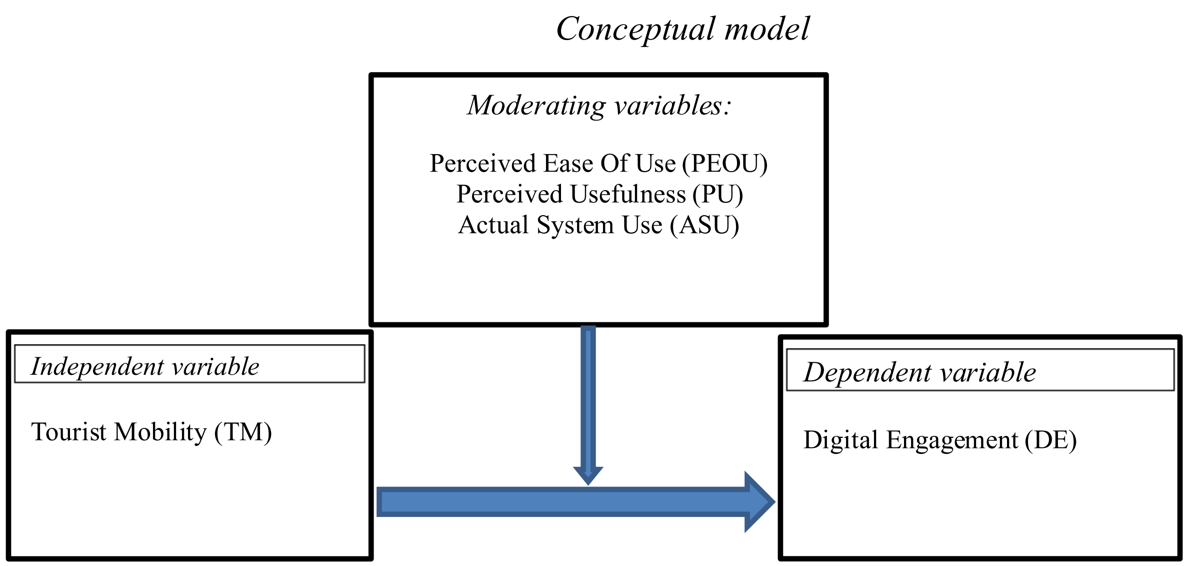

Figure 1: Conceptual Model Research

From the conceptual framework, the following hypotheses can be derived:

- There is a positive relationship between TM on one side and DE on the other side.
- PEOU, PU and ASU influence the relationship between TM and DE in a positive way.

The dataset of geospatial movement and online interaction histories of tourists was analyzed to measure individual mobility and engagement levels. The data set was standardized by renaming all column names to lowercase and by proper formatting. Mobility was measured in terms of the total distance traveled by each tourist, calculated by using the geodesic distance between consecutive observed points (Weber & Péclat, 2017). Each visitor's path of movement was reconstructed and summed as a cumulative travel distance measure for each. Digital engagement was also calculated by the number of observed interactions per visitor in the dataset, such as interactions across different online platforms, representing levels of engagement.

Correlation analysis was used to test the relationship between tourist mobility and digital engagement (Duncan & Earhart, 2011). Highly mobile tourists should have greater levels of DE. A two-sample t-test was conducted to compare high-mobility and low-mobility tourist engagement levels. In order to analyze digital engagement behaviors of tourists better, we applied SNA to tourist mobility and engagement data. The data, collected from an IoT-based tracking system, contained geospatial and temporal records of movement by tourists. Interactions were identified based on spatiotemporal proximity. Two tourists were deemed to have interacted, if their timestamps were within a difference of 24 hours (time threshold) and if they were within 50 km (distance threshold), which calculated based on the Haversine formula to obtain precise geospatial distance estimates (Muttaqin et al., 2024).

4 Results

4.1 Preliminary Results

As stated before, the data preprocessing produced an integrated dataset showing tourist mobility and engagement behaviors across multiple dimensions. The output dataset contained structured records with sanitized and aligned timestamps to analyze tourist movement accurately over time. GPS-data preserved geospatial truth after the elimination of anomalies, while Wi-Fi connection logs provided high-resolution information about tourist dwell time at tourist areas. Mobile app usage statistics were structured to reflect actual interactions, so only human-generated activities were considered. The smart card transaction records kept genuine transport usage patterns, and social media interaction logs actually reflected user behavior after eliminating artificial activity.

Descriptive statistics also captured high variations in tourist mobility between different locations. GPS tracking points distribution showed cluster movement in tourist urban areas, and transport data showed preferred modes of travel. As expected, Wi-Fi connection patterns showed peak usage in hospitality and commercial zones. Mobile app logs validated high dependency on navigation and booking websites, validating the use of digital resources in trip planning. Social media interaction patterns revealed varying degrees of engagement across different tourist locations, with more activity observed in visually salient regions. The successful integration of these disparate datasets provided a firm foundation for advanced analysis, including profiling clustering of tourists, predicting movement patterns, and measuring online engagement trends.

4.2 Technology Acceptance Model (TAM) Analysis

The correlation analysis confirmed the existence of the hypothetical positive relationship between PU and DE (correlation coefficient of $r = 0.064$ and a statistically significant p-value of 0.013). This implies that tourists who perceive IoT applications as useful, employ digital platforms more frequently. PEOU had a less significant correlation ($r = 0.051$, $p = 0.476$), which suggests that ease of use is not the central driver of engagement. ASU had a weak correlation ($r = 0.010$, $p = 0.009$), and it implies that frequency of use does not always lead to engagement. The regression analysis also supports these findings, with the slope of the regression line between PU and DE being sharper than the one for PEOU and DE, reinforcing the more significant role played by perceived usefulness in tourist engagement.

Table 1: Correlation Analysis Between 3 Moderating Variables and Digital Engagement

Variable	Correlation with Digital Engagement (r)	P-Value
Perceived Ease of Use (PEOU)	0.051	0.476
Perceived Usefulness (PU)	0.064	0.013
Actual System Use (ASU)	0.010	0.009

The findings emphasize that although ease of use is a factor in engagement, perceived ease of using digital services is the key driver for tourists engaging with IoT-based platforms.

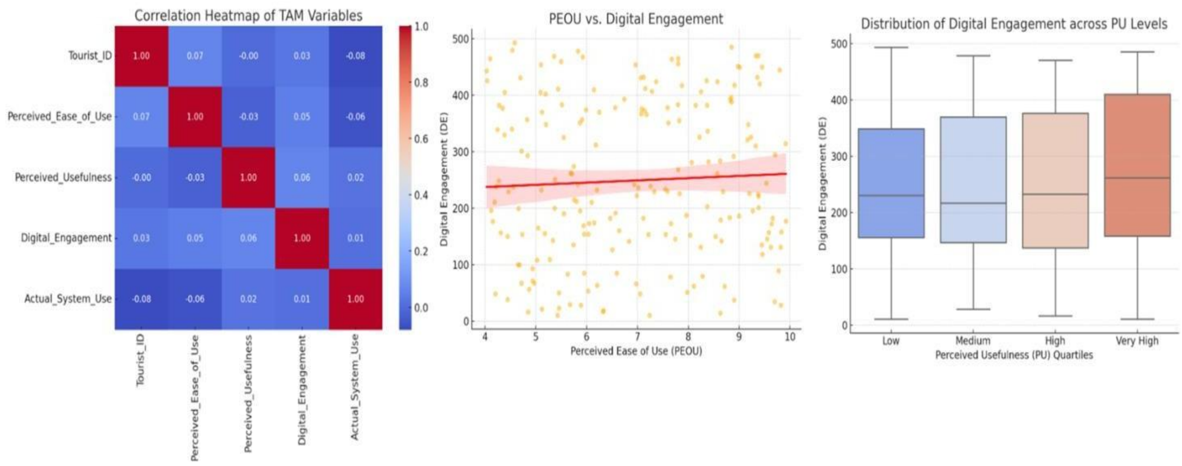

Figure 2: Correlation Matrix, Scatter Plot of PEOU vs. DE and box plot of DE by PU levels.

4.3 Social Network Analysis (SNA)

The network graph was able to identify the most intense tourist engagement patterns. The top five influencers, based on degree centrality are mentioned in Table 2. We use the term “influencers” in the context of network centrality, not in the social media or behavioral psychology sense. These tourists were identified through Degree

Centrality in the interaction graph, meaning they had the highest number of spatiotemporal encounters with other tourists. In network theory, a node with high degree centrality is typically considered structurally influential, as it connects with many others and plays a key role in network connectivity and information flow. These tourists had the highest number of interactions, indicating their important contribution to digital and physical interaction in the destination. The network structure had clearly defined clusters, which were an indication of localized patterns of engagement among tourists. Community detection analysis revealed well-defined subgroups, which were most likely a reflection of similar itineraries or common destinations of interest.

Table 2: Tourist with highest connectivity in social network

Tourist ID	Degree Centrality
4170	0.0058
3444	0.0043
2312	0.0043
1364	0.0043
2687	0.0043

The graph visualization supports the fact that tourist interactions were not evenly distributed but focused in a few highly active nodes

Figure 3: The tourist engagement network graph revealing key tourist engagement patterns. The findings highlight influential tourists as key drivers of engagement and imply potential uses in targeted marketing, customized tourism experiences, and crowd management planning.

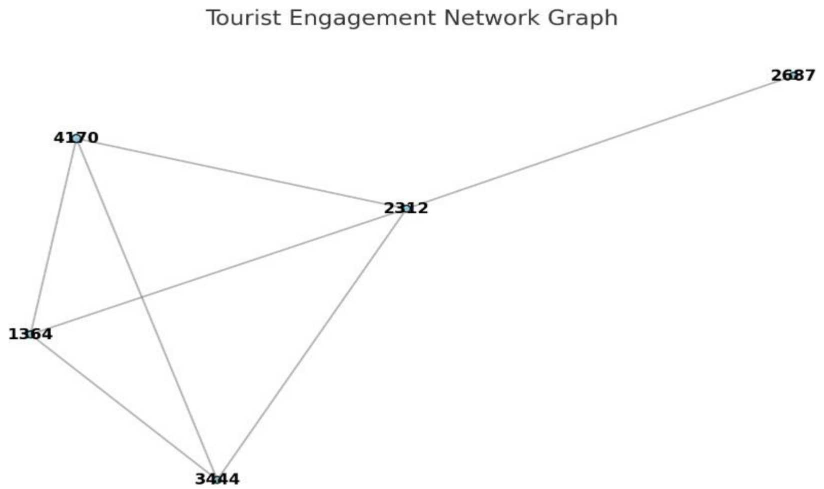

Figure 3: The tourist engagement network graph revealing key tourist engagement patterns.

4.4 Hypothesis Testing

The results from the statistical analysis reveal a strong positive correlation between tourist mobility and digital engagement. A summary of key findings is presented in Table 3: Hypotheses Testing Results

Table 3: Hypotheses Testing Results

Statistical Test	Value	Interpretation
Pearson Correlation (r)	0.8758	Strong positive correlation between mobility and engagement
P-value (Correlation)	0.0000	Statistically significant ($p < 0.05$)
T-test (t-value)	68.8592	Significant difference in engagement between high and low mobility tourists
P-value (T-test)	0.0000	Statistically significant ($p < 0.05$)

These findings indicate that tourists with higher mobility levels are more likely to be actively engaged in digital platforms. The statistical significance ($p < 0.05$) confirms that this relationship is not due to random chance. Figure 4 demonstrates the correlation found and graphically discriminates patterns of engagement in high-mobility and low-mobility tourists. Significant t-test outputs also validate further that more mobility among tourists also yields higher engagement levels. Results give empirical endorsement to the research hypothesis that more mobility is highly tied to digital engagement with the provision of information on tourists' interaction modes with online entities in relation to their mobility styles.

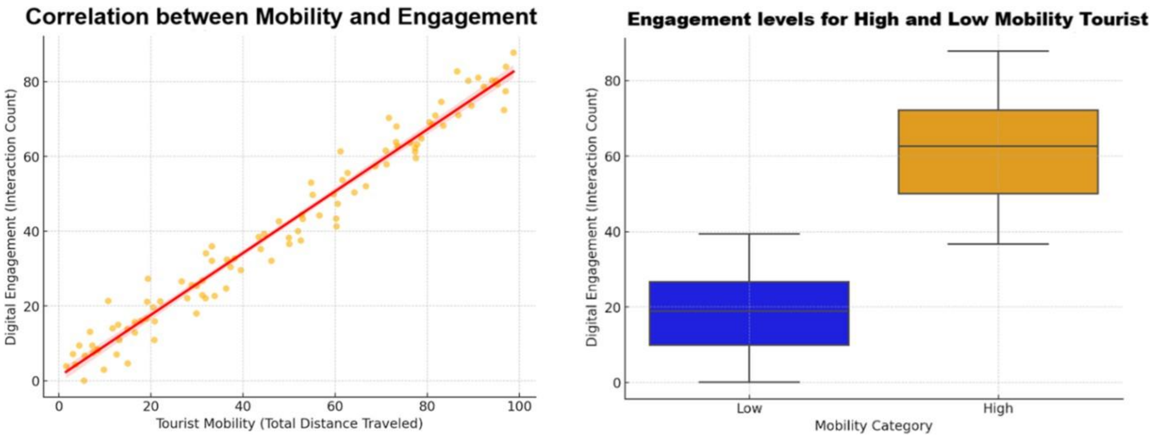

Figure 4: Correlation and patterns of engagement for high-mobility and low-mobility tourists.

5 Discussion

The application of IoT in tourism analytics has revolutionized the comprehension of tourist mobility and digital engagement. By utilizing actual-time data compilations and computational methods, the current research offers a more profound insight into how tourists interact with online platforms and travel between destinations on a local scale in inner city environments. The results are informative data concerning regularities in behavior. The most influential tourists at the forefront were those tourists who had the highest degree centrality, indicating they are likely to spread travel news and interact with online material. This finding is compatible with studies that emphasize the role of online word-of-mouth in travel decisions (Pennisi, 2019).

However, the relatively low centrality scores indicate that while there are certain tourists with a higher probability of interacting, the network is rather decentralized as a whole. This result makes one think that tourism engagement is spread among many actors rather than being dominated by a few, which contradicts findings from more established digital marketing studies where influencers have significantly higher centrality (Malinen & Koivula, 2020). A possible reason is that tourist encounters are more fluid and dynamic, restraining the creation of fixed influencer chains.

We found a high positive correlation between mobility behavior and digital activity. This supports the hypothesis that increased movement across destinations is associated with heightened digital activity. This result is consistent with previous studies. (Lim et al., 2019). However, the causality remains uncertain. Does mobility of tourists drive engagement, or do digitally engaged tourists tend to explore more locations? Future research should explore this potential bi-directional relationship through longitudinal data tracking. The results further show a highly significant difference in engagement levels between high-mobility and low-mobility tourists. This aligns with existing frameworks that suggest that mobile tourists rely more on real-time digital support to navigate unfamiliar destinations (Emmanouilidi et al., 2013). However, an alternative interpretation could be that digitally engaged tourists are inherently more adventurous, leading to an incidental correlation rather than a direct causal link. Additional studies incorporating experimental interventions could clarify this assumption.

The analysis of the use of social networks by tourist also identifies essential nodes in the engagement network, offering practical insight for stakeholders in tourism. This research gives strong indications that destination management companies can leverage mobility data to forecast and drive engagement patterns successfully. Combining these insights, policymakers can create focused marketing efforts and infrastructure development that responds to the changing needs of technologically engaged tourists.

6 Conclusion

This study deepens the insight into the relationship between TM tourist mobility and DE behavior using IoT-driven analytical methods. Our findings prove that DE is tightly linked to tourist mobility patterns, marking mobile tourists as significant influencers in the online world. The research confirmed also the existence of the hypothetical positive relationship between perceived usefulness and digital engagement. This implies that tourists who perceive IoT applications as useful employ digital platforms more frequently. The PEOU was weakly linked to digital engagement. This suggests that ease of use is not the central driver of engagement of tourists. We also found a weak correlation for actual system use and this means that the frequency of use does not always lead to digital engagement. An executed regression analysis supports these findings. The findings emphasize that although ease of use is a factor in engagement, perceived ease of using digital services is the key driver for tourists engaging with IoT-based platforms.

Because of the computations to define the tourist, some limitations have to be mentioned. First of all, the data used to define what a tourist is are neither actively provided nor confirmed by the individual to whom the data belong. The data might also apply to other categories of people in the same environment, like small business owners with a fixed or mobile shop who focus on tourists as customers. Another important aspect that is missing because of the used methodology is knowledge about digital engagement before the travel took place. With sufficient information about the tourism destination, tourists may not need (much more) additional information on the actual spot. There might also be a difference between tourists in digital skills and use in general, based on age, availability of network and general use of digital services in the home country, or price of mobile phones and internet access.

Another limitation is that the analysis is based on observational data, which means that causal inference is restricted. Experimental methodologies should be included in future studies to test interventions that potentially affect mobility and engagement patterns. The study mainly deals with digital engagement measures without examining qualitative dimensions of tourist experiences, like satisfaction or emotional response. Additionally, the strong correlation between mobility and digital engagement underscores the importance of enhancing digital touch points such as geo location services, augmented reality navigation, and personalized content delivery.

The results of this study may benefit a number of beneficiaries, such as policy makers, entrepreneurs, and researchers. For policy makers, the research underscores the need for investments in infrastructure that enables frictionless digital experiences. Since mobile tourists are found to have high involvement, having strong internet connectivity, incorporating IoT sensors for real-time travel information, and creating data-driven decision support systems could prove highly effective at boosting visitor satisfaction and economic yield. Real-time intervention approaches need to be researched in the future to better optimize tourist experiences and economic impacts. Future research may also involve sentiment analysis and qualitative surveys to better comprehend the behavior of tourists. Further research in this field might consider testing predictive models in various tourism settings. Also, pre-travel activities might also consider in examining this relationship. In conclusion, our research presents a sound and scientific model for interpreting the relationship between tourist mobility and online engagement, building upon the literature of smart tourism analytics. With the bridging of the existing gap between applications of IoT and insights into tourist behavior, more data-driven and individualized forms of tourism become a reality for the digital world.

References:

Abbas-Aghababazadeh, F., Li, Q., & Fridley, B. L. (2018). Comparison of normalization approaches for gene expression studies completed with high-throughput sequencing. *PloS one*, *13*(10), e0206312. [CrossRef]

Al Kurdi, B., Alshurideh, M., Salloum, S., Obeidat, Z., & Al-dweeri, R. (2020). An empirical investigation into examination of factors influencing university students' behavior towards elearning acceptance using SEM approach. *International Journal of Interactive Mobile Technologies (IJIM)*, 14(02), 19. [CrossRef]

Ali, S. (2025). Exploring the Mediating Role of Behavioral Intention in the Relationship between Social Media Tourism Promotion, Social Media Tourism Searches, and Tourist Behavior in Pakistan. *The Critical Review of Social Sciences Studies*, 3(1), 2685-2696. [CrossRef]

Attfield, S., Kazai, G., Lalmas, M., & Piwowarski, B. (2011, February). *Towards a science of user engagement (position paper)*. In *WSDM workshop on user modelling for Web applications* (Vol. 1).

Bouvier, P., Lavoué, E., & Sehaba, K. (2014). Defining engagement and characterizing engaged-behaviors in digital gaming. *Simulation & Gaming*, 45(4-5), 491-507. [CrossRef]

Car, T., Stifanich, L. P., & Šimunić, M. (2019). Internet of things (iot) in tourism and hospitality: Opportunities and challenges. *Tourism in South East Europe*, *5*(3), 163-175. [CrossRef]

Cerutti, S., & Piva, E. (2016). The role of tourists' feedback in the enhancement of religious tourism destinations. *International journal of religious tourism and pilgrimage,* 4(3), 4.

Chen, C.-C., & Tsai, J.-L. (2019). Determinants of behavioral intention to use the Personalized Location-based Mobile Tourism Application: An empirical study by integrating TAM with ISSM. *Future Generation Computer Systems*, *96*, 628-638. [CrossRef]

Chen, J., Becken, S., & Stantic, B. (2022). Harnessing social media to understand tourist mobility: The role of information technology and big data. *Tourism Review*, *77*(4), 1219-1233. [CrossRef]

Chong, A. Y. L., Khong, K. W., Ma, T., McCabe, S., & Wang, Y. (2018). Analyzing key influences of tourists' acceptance of online reviews in travel decisions. *Internet Research,* 28(3), 564-586. [CrossRef]

Davis, F.D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13, 319-340. [CrossRef]

De Cristofaro, C. (2023). *Leveraging Wikidata to highlight differences in topics and countries on Instagram Social Network* Politecnico di Torino].

Dickinson, J. E., Ghali, K., Cherrett, T., Speed, C., Davies, N., & Norgate, S. (2014). Tourism and the smartphone app: Capabilities, emerging practice and scope in the travel domain. *Current issues in tourism,* 17(1), 84-101. [CrossRef]

Drummond, C., O'Toole, T., & McGrath, H. (2020). Digital engagement strategies and tactics in social media marketing. *European Journal of Marketing*, 54(6), 1247-1280. [CrossRef]

Duncan, R. P., & Earhart, G. M. (2011). Measuring participation in individuals with Parkinson disease: relationships with disease severity, quality of life, and mobility. *Disability and rehabilitation*, *33*(15-16), 1440-1446. [CrossRef]

Dutta, S., Dixit, S., & Khare, A. (2024). Examining 360° video tourist experiences and adoption in a developing country. *Qualitative Market Research: An International Journal*, 28(2), 209–233. [CrossRef]

Elhanashi, A., Dini, P., Saponara, S., & Zheng, Q. (2023). Integration of deep learning into the iot: A survey of techniques and challenges for real-world applications. *Electronics*, *12*(24), 4925. [CrossRef]

Emmanouilidis, C., Koutsiamanis, R.-A., & Tasidou, A. (2013). Mobile guides: Taxonomy of architectures, context awareness, technologies and applications. *Journal of network and computer applications*, *36*(1), 103-125. [CrossRef]

Ficili, I., Giacobbe, M., Tricomi, G., & Puliafito, A. (2025). From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI. *Sensors*, *25*(6), 1763. [CrossRef]

Gupta, P., & Bagchi, A. (2024a). Data Manipulation with Pandas. In *Essentials of Python for Artificial Intelligence and Machine Learning* (pp. 197-235). Springer.

Gupta, P., & Bagchi, A. (2024b). Introduction to NumPy. In *Essentials of Python for Artificial Intelligence and Machine Learning* (pp. 127-159). Springer.

Hahsler, M., Piekenbrock, M., & Doran, D. (2019). *dbscan: Fast density-based clustering with R.*

Han, S., & Kwak, I.-Y. (2023). Mastering data visualization with Python: practical tips for researchers. *Journal of Minimally Invasive Surgery*, *26*(4), 167. [CrossRef]

Hietajärvi, L., Maksniemi, E., & Salmela-Aro, K. (2022). Digital engagement and academic functioning. *European Psychologist*, 27(2), 102–115. [CrossRef]

Javed, M., Tučková, Z., & Jibril, A. B. (2020). The role of social media on tourists' behavior: An empirical analysis of millennials from the Czech Republic. *Sustainability*, 12(18), 7735. [CrossRef]

Kim, J., Fesenmaier, D. R., & Johnson, S. L. (2013). *The effect of feedback within social media in tourism experiences. In Design, User Experience, and Usability. Web, Mobile, and Product Design*: Second International Conference, DUXU 2013, Held as Part of HCI International 2013, Las Vegas, NV, USA, July 21-26, 2013, Proceedings, Part IV 2 (pp. 212-220). Springer Berlin Heidelberg.

Lee, C., Richardson, S., Goh, E., & Presbury, R. (2023). From the tourist gaze to a shared gaze: Exploring motivations for online photo-sharing in present-day tourism experience. *Tourism Management Perspectives*, *46*, 101099. [CrossRef]

Lim, K. H., Chan, J., Karunasekera, S., & Leckie, C. (2019). Tour recommendation and trip planning using location-based social media: A survey. *Knowledge and Information Systems*, *60*, 1247-1275. [CrossRef]

Ling, L. T. (2017). *The impacts of system quality and information quality on mobile users' behavioral intentions to use trade show application systems in Hong Kong: The mediating effects of perceived ease of use and perceived usefulness* Doctoral dissertation, The University of Newcastle, Australia].

Lukita, C., Pangilinan, G. A., Chakim, M. H. R., & Saputra, D. B. (2023). Examining the impact of artificial intelligence and internet of things on smart tourism destinations: A comprehensive study. *Aptisi Transactions on Technopreneurship (ATT)*, *5*(2sp), 135-145. [CrossRef]

Magurano, D. (2018). *Development of a scalable architecture for Industrial Internet of Things*

Malinen, S., & Koivula, A. (2020). Influencers and targets on social media: Investigating the impact of network homogeneity and group identification on online influence. *First Monday*. [CrossRef]

Massaron, L., & Boschetti, A. (2016). *Regression analysis with Python*. Packt Publishing Ltd. Miller, H. J. (2021). Activity-based analysis. *Handbook of regional science*, 187-207.

Mohammadi, M., Al-Fuqaha, A., Sorour, S., & Guizani, M. (2018). Deep learning for IoT big data and streaming analytics: A survey. *IEEE Communications Surveys & Tutorials*, *20*(4), 2923-2960. [CrossRef]

Morales, R. C., Gamboa, J., Nguyen, B., Siddiqui, O., & Bonsall, J. (2021). *Accuracy and Validation of Geotab GPS Fleet Tracking Devices* (0148-7191).

Morrison, L. G., Yardley, L., Powell, J., & Michie, S. (2012). What design features are used in effective e-health interventions? A review using techniques from critical interpretive synthesis. *Telemedicine and e-Health*, *18*(2), 137-144. [CrossRef]

Muttaqin, A., Murtopo, A. A., Syefudin, S., & Gunawan, G. (2024). Application of the haversine formula method to determine the closest distance to a minimarket. *Jurnal Mandiri IT*, *13*(1), 72- 80.

Nowak, R. B., Alimohamadi, H., Pestonjamasp, K., Rangamani, P., & Fowler, V. M. (2022). Nanoscale dynamics of actin filaments in the red blood cell membrane skeleton. *Molecular biology of the cell*, *33*(3), ar28. [CrossRef]

Nunes, C. A. d. E. S. (2022). *Public transport management systems with real-time passenger information* Universidade de Évora].

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American society for Information Science and Technology*, *59*(6), 938-955. [CrossRef]

Ortiz, B. L., Gupta, V., Kumar, R., Jalin, A., Cao, X., Ziegenbein, C., Singhal, A., Tewari, M., & Choi, S. W. (2024). Data preprocessing techniques for ai and machine learning readiness: Scoping review of wearable sensor data in cancer care. *JMIR mHealth and uHealth*, *12*(1), e59587. [CrossRef]

Park, S., Zu, J., Xu, Y., Zhang, F., Liu, Y., & Li, J. (2023). Analyzing travel mobility patterns in city destinations: Implications for destination design. *Tourism Management*, *96*, 104718. [CrossRef]

Paul, A., Woolley, M., Jaafari, M., & Handal, J. (2024). *Cisco Meraki Fundamentals: Cloud- Managed Operations*. Cisco Press.

Pennisi, F. (2019). The Role of Culture in Word-of-Mouth Generation and Online Reviews. *The Example Of Travel & Tourism Service*.

Pop, R.-A., Săplăcan, Z., Dabija, D.-C., & Alt, M.-A. (2022). The impact of social media influencers on travel decisions: The role of trust in consumer decision journey. *Current issues in Tourism*, *25*(5), 823-843. [CrossRef]

Rifat, M. R., Moutushy, S., Ahmed, S. I., & Ferdous, H. S. (2011). *Location based Information system using OpenStreetMap*. 2011 IEEE Student Conference on Research and Development.

Rodgers, S., & Thorson, E. (2018). Special issue introduction: Digital engagement with advertising. *Journal of Advertising,* 47(1), 1-3. [CrossRef]

Sánchez-Franco, M. J., & Rey-Tienda, S. (2024). The role of user-generated content in tourism decision-making: an exemplary study of Andalusia, Spain. *Management Decision*, *62*(7), 2292- 2328. [CrossRef]

Shafiezad, O., & Mostofi, H. (2024). Sentiment Analysis of Berlin Tourists' Food Quality Perception Through Artificial Intelligence. *Tourism and Hospitality*, *5*(4), 1396-1417. [CrossRef]

Shu, H., Pei, T., Song, C., Chen, J., Chen, X., Guo, S., Liu, Y., Wang, X., Wang, X., & Zhou, C. (2022). Density-based clustering for bivariate-flow data. *International Journal of Geographical Information Science*, *36*(9), 1809-1829. [CrossRef]

Singh, S., & Srivastava, P. (2019). Social media for outbound leisure travel: a framework based on technology acceptance model (TAM). *Journal of Tourism Futures*, *5*(1), 43-61. [CrossRef]

Toms, S., Crickard, P., & Van Rees, E. (2018). *Mastering geospatial analysis with Python: explore GIS processing and learn to work with GeoDjango, CARTOframes and MapboxGL-Jupyter*. Packt Publishing Ltd.

Tonin, G. (2015). Uber: Disruptive innovation and regulation challenges.

Viennot, N., Garcia, E., & Nieh, J. (2014). *A measurement study of google play*. The 2014 ACM international conference on Measurement and modeling of computer systems,

Volo, S., & Irimiás, A. (2022). *Consumer behavior in e-Tourism*. In Handbook of e-Tourism (pp. 119-139). Springer.

Vu, H. Q., Li, G., Law, R., & Zhang, Y. (2018). Tourist activity analysis by leveraging mobile social media data. *Journal of travel research*, *57*(7), 883-898. [CrossRef]

Wang, D., Park, S., & Fesenmaier, D. R. (2012). The role of smartphones in mediating the touristic experience. *Journal of travel research,* 51(4), 371-387. [CrossRef]

Wang, D., Xiang, Z., & Fesenmaier, D. R. (2016). Smartphone use in everyday life and travel. *Journal of travel research,* 55(1), 52-63. [CrossRef]

Weber, S., & Péclat, M. (2017). Weber, S., & Péclat, M. (2017). A Simple Command to Calculate Travel Distance and Travel Time. *The Stata Journal: Promoting Communications on Statistics and Stata,* 17(4), 962–971. [CrossRef]

Yardley, L., Spring, B. J., Riper, H., Morrison, L. G., Crane, D. H., Curtis, K., ... & Blandford, A. (2016). Understanding and promoting effective engagement with digital behavior change interventions. *American journal of preventive medicine,* 51(5), 833-842. [CrossRef]

Yu, X., Anaya, G. J., Miao, L., Lehto, X., & Wong, I. A. (2018). The impact of smartphones on the family vacation experience. *Journal of Travel Research,* 57(5), 579-596. [CrossRef]

Zhang, H., & Dai, L. (2018). Mobility prediction: A survey on state-of-the-art schemes and future applications. *IEEE access*, *7*, 802-822. [CrossRef]