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Preface

The rapid evolution of ICTs has fundamentally reshaped the landscape of travel, tourism, and hospitality. Over the past three decades, the ENTER eTourism conference has served as a home for scholars, industry practitioners, and technology developers, providing a platform for critical discourse on how emerging technologies influence the tourism domain. As we look toward 2060, we must recognize that the next three decades will likely bring even more profound transformations than the past thirty years combined. The rise of artificial intelligence, service robotics, the Internet of Things (IoT), extended realities (XR), and other disruptive innovations necessitates both careful scrutiny and bold vision-setting.

This year's ENTER conference, eTourism Towards 2060, challenges our community to collectively envision the long-term future of technology in travel, tourism, and hospitality. While ICTs continue to enhance efficiency, personalization, and engagement, they also raise fundamental questions, for instance about ethical responsibility, labor displacement, and the societal impact of automation. For instance, if language model based chatbots misinterpret booking & cancellations policies – as was the case with Air Canada in 2022, resulting in the bot promising terms & conditions that did not exist – who should be held liable?

This volume of conference proceedings captures the latest research, insights, and discussions from leading minds in eTourism, bringing together interdisciplinary perspectives from academia, industry, and policymaking. In particular, the Working Paper Track contributions presented here explore how AI-driven systems redefine tourism services, how IoT and smart technologies enhance destination management, and how XR can transform the tourist experience, among many other interesting topics. As we navigate the road to 2060, it is crucial to not only harness technological innovations but also ensure they align with human-centric values, sustainability goals, and the evolving needs of travelers and tourism businesses. To that end, the ENTER conference aims to provide actionable insights for all stakeholders—from researchers and educators to policymakers, entrepreneurs, and hospitality professionals—so that we may collectively shape a future where technology serves as an enabler of positive transformation.

On behalf of the International Federation for IT and Travel & Tourism (IFITT) and IFITT Poland, we extend our sincere gratitude to all contributors, reviewers, and participants who make this knowledge exchange possible. We hope that the discussions sparked during and after the conference will inspire continued innovation, collaboration, and responsible leadership in the field of eTourism. The journey to 2060 begins today, and together, we can chart a course toward a smarter, more sustainable, and more inclusive future for tourism.

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Section 1: Sustainability

Clustering Territorial Units Upon Tourism Seasonality Patterns Based on Mobile Phone Time Series Data

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Abstract. Tourism influences economies, societies, and whole environments. In terms of negative effects, tourist arrival peaks put temporary pressure on destinations. Thus, it is important to identify seasonality patterns of homogeneous regions to guide DMOs in the formation of development plans for broader geographical areas. Monthly mobile phone time series tracked from 01/2022 to 12/2023 for Friuli-Venezia-Giulia (FVG) were examined to group municipalities along seasonality patterns using dynamic time warping (DTW) and hierarchical cluster analysis (HCA) to draw conclusions at the sub-regional level.

Keywords: Seasonality, Mobile Phone Data, Time Series Clustering, DTW.

1   Introduction and Background

The impact of tourism on the socioeconomic and environmental basis of destinations is widely discussed [1, 2]. It has been shown that seasonality effects intensify the negative impacts on the destinations' carrying capacity [3] which makes it a crucial component for tourism predictions. Analyses of tourist flows help to identify tourist concentrations during certain periods of the year [4]. Therefore, knowledge about seasonality patterns is elementary for single destinations to monitor and advance tourism development strategies. As this also applies to broader geographical areas, segmentation is needed to understand the effects on the wider destination. But this task comes with several pitfalls.

Common indices like Gini and Theil do not consider ordinal and cyclical structures of time periods [5]. Hence, decomposition into seasonal pattern and magnitude changes [6], or multiplicative trend-cycle, seasonal, and residual components were suggested and Euclidean distances between them handed over to HCA [5]. However, such distances depend on equal time intervals, and are prone to noise and outliers [7].

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In addition, Euclidean distances or correlations between value pairs of single time points exclude autocorrelation arguments. Likewise, piecewise linear functions include local trends of two consecutive time points but ignore global trends [8]. Autoregressive (AR) metrics resolve this problem but are not suited for time series with a limited time range [9]. Short time series of Italian tourist areas were clustered combining spline interpolation with k-means [10]. Similarly, tourist arrival time lags from AR models were split to reduce complexity before analyzing clusters separately, simplicity and fast convergence were arguments in favor of k-means [11]. But k-means might not result in global optima, is prone to initialization [12], invariant to transformations altering the sequence of observations [13] and cannot handle local time shifting of periods out of phase [14]. A shift of one time series increases Euclidean distances although two time series might be similar in shape [7]. Alternatively, horizontal visibility graphs were proposed to transform Italian monthly overnights into networks and gain insight into periodicity, fractality, and chaoticity [15], but miss regional segmentation. In combination with DTW, partitioning around medoids and HCA are most popular, whereby the latter is preferred due to visualizations of nested clusters [11]. As DTW distances can handle scale, warping, and phase invariances [16], we classify tourist destinations upon DTW distances between short mobile phone time series using HCA with Ward's D2 method.

2 Methodology

2.1 Mobile Phone Time Series Data and Spatial Maps

Italy is organized in 20 regions, one is FVG. It captures the northeastern part of Italy, and covers four provinces, Gorizia, Udine, Pordenone, and Trieste. As official statistics from commercial lodging facilities exclude overnights with friends and relatives [5], or the sharing economy, monthly time series of mobile phone users who dialed in to a cellphone transmitter station from 0:00-8:00, 8:00-16:00, or 16:00-0:00, were tracked by the mobile phone base stations located in FVG from 01/2022 to 12/2023. If registered from 16:00-0:00 and 0:00-8:00 the next day, it was concluded that the user stayed overnight. Users were further categorized into intercontinental (outside Europe), European (not Italian), national (Italian but not FVG), regional (FVG), the four

FVG provinces, and residents/city users of the municipality. The first three were merged. They represent mobile phone users who travel to a municipality and stay overnight, but do not live in FVG, as of now called 'visitors'. As mobile phone data were not available for all 215 FVG municipalities, 14 municipality pairs and one triple were merged. This results in 200 polygons tagged with the visitors' user behavior time series.

2.2 Dynamic Time Warping (DTW)

DTW [16, 17, 18] was used to determine the distances between the municipalities' time series, $d_\emptyset(X, Y)$. If two time series follow a comparable shape, DTW will judge them as being similar. DTW's advantage lies in non-linear alignments due to its freedom of stretching and/or shifting temporal peaks by time point duplications. First, cross-distance matrices are computed for each municipality pair capturing the distances between all possible time point combinations of two time series, $X = x_1, \dots, x_N$ and $Y = y_1, \dots, y_M$. Second, the minimum accumulated weighted distances through the distance-matrices are determined, the optimal warping curves, $\emptyset_x(k)$ and $\emptyset_y(k)$, formula (1).

$$d_\emptyset(X, Y) = \sum_{k=1}^{T} d(\emptyset_x(k), \emptyset_y(k)) m_\emptyset(k) / M_\emptyset \qquad (1)$$

Following specifications reduce computational complexity and increase effectiveness:

- **Z-Normalization**. As the focus is put on cyclical trends of visitor shapes, absolute visitor numbers are neutralized using Z-transformation, standardization, $Z=(X-\mu)/\sigma$.
- **Warping Window**. If set to zero, no alignment (duplication of time points) is allowed. As the focus lies on the frequency/distribution of peaks no constraint was set. Instead, an unlimited number of consecutive time points of X can be matched with a single time point of Y, and vice versa. Both time series can be stretched/shifted.
- **Monotonicity Constraint**. To preserve the time order and the sequence of seasonal fluctuations, the warping path indices need to increase monotonically.
- **Boundary Condition**. As all time series have the same length, open-ended warping paths are not applicable here. To provide for endpoint

invariance, all warping curve pairs, $\emptyset_x(k)$ and $\emptyset_y(k)$, are linked in January 2022 (start) and December 2023 (end).

- **Continuity Constraint**. Transitions are limited to adjacent time points. Skipping time points is not permitted. All elements of X must be matched with elements of Y, and vice versa.

- **Step Pattern** definitions influence the warping path steps through the cross-distance matrices. *Symmetric1* (White-Neely), and *symmetric2* are most well-known. *Symmetric1* favors direct transitions and equally weights all steps with a value of 1. *Symmetric2* compensates for side steps and weights diagonal steps with a value of 2, no penalty for time point duplications. As asymmetric patterns limit alignments in terms of time expansion or end point constraints, *symmetric2* was chosen (Fig.1).

Fig. 1. Symmetric2 step pattern.

- **Normalization.** The sum of distances × step pattern weights is divided by the sum of the two time series lengths, $M_\emptyset$, $N + M$. This gives the average distance.

2.3   Clustering, Validation, and Entropy

A matrix containing DTW-distances between all municipalities was processed using HCA with Ward's D2 for time series clustering. Four internal cluster maximization metrics (Silhouette – Sil, Dunn – D, Calinski-Harabasz – CH, and Score Function – SF), and three minimization metrics (COP, Davies-Bouldin – DB, and the Modified Davies-Bouldin DB*) were used to evaluate the 2 to 25 cluster solutions. The adjusted rand index (ARI) was determined to compare different partitions based on their similarity corrected for chance. The minimal spanning tree graph was used as input for the k-nearest neighbor graph (MST-kNN) to automatically reveal the number of clusters.

3 Results

The number of visitors per month and municipality ranged between 32 (Cercivento 01/2022), and 645,461 (Trieste 08/2023). Fig. 2 exemplifies the optimal warping path through a cross-distance matrix of two municipalities. Stretches are signalized by deviations from the main diagonal. Such alignments are visible if dotted lines in Fig. 3 connect single time points of one time series with multiple time points of the other time series. The solid line in Fig. 3 represents the time series of Aiello del Friuli, the dashed line the time series of Amaro.
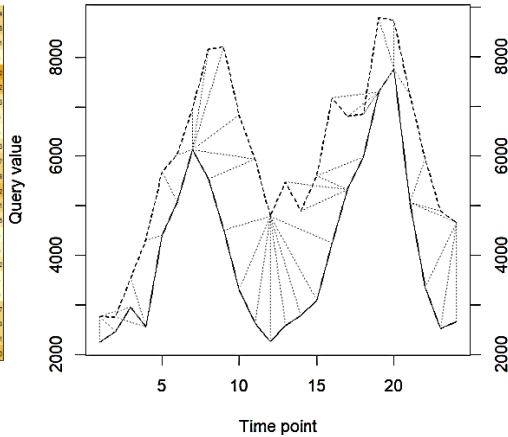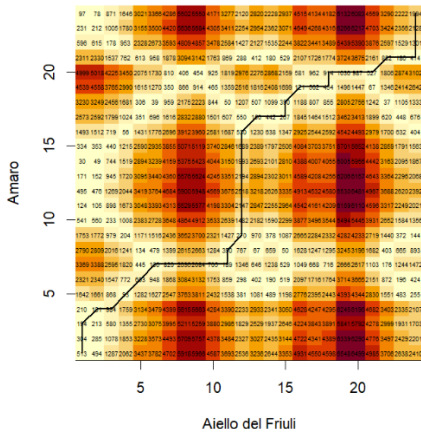
Fig. 2. Warping path through the cross-distance matrix of two municipalities.

Fig. 3. DTW alignment between Aiello del Friuli and Amaro.

DTW distances between the mobile phone time series were clustered using HCA to group municipalities. MST-kNN, Sil, DB, and DB* favors 5 clusters. COP strongly declines from 5 to 6 clusters. CH levels off at around 4 to 6 clusters. D favors 4 clusters. SF reveales no visible changes after a sharp drop to 3 clusters. ARI shows greater similarity between the 4 and 5 cluster solutions compared with the 5 and 6 cluster solutions. Justified by statistical means, most indices point towards 5 clusters. Fig. 4 visualizes the cyclical trends and Fig. 5 their territorial distribution revealing homogeneous subregions: 1) one extreme annual peak/upward trend (91 municipalities), 2) on extreme peak/flat trend (38), 3) two peaks (4), 4) weak seasonality/upward trend (20), and 5) one medium seasonality peak/increasing trend (43).
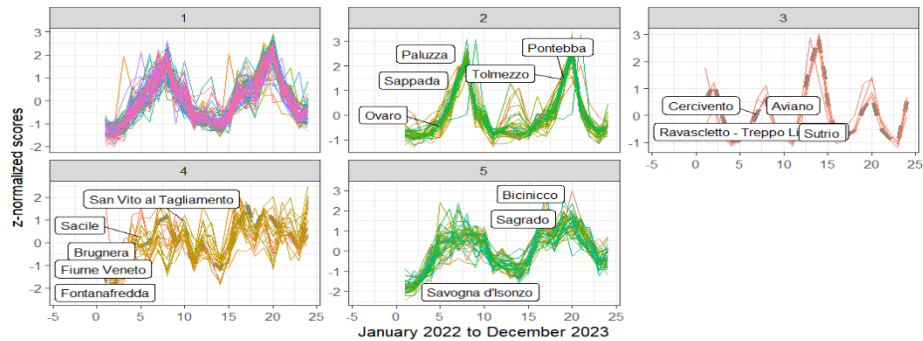
Fig. 4. Seasonality trend clusters.
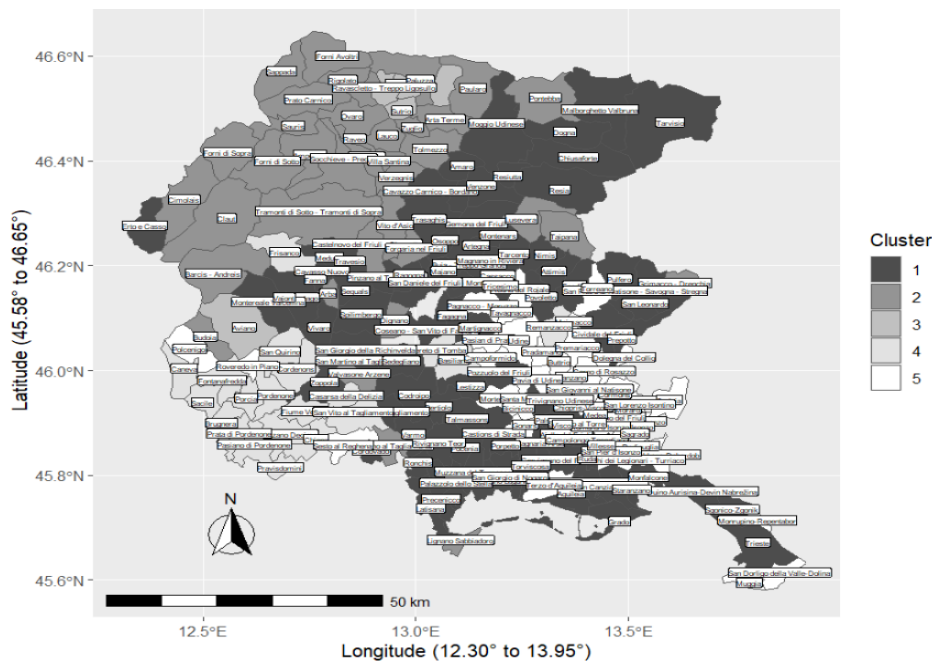
Fig. 5. Seasonality patters in the FVG region.

4 Discussion and Future Implications

FVG is organized in six tourism regions, 1) Trieste and Karst (nature tourism and Trieste region), 2) Gorizia, the Isonzo Karst and Collio area (historical routes and wine region), 3) Cividale and Natisone Valleys (incl. the UNESCO World Heritage Site), 4) the plains and hills of Friuli (with Udine), 5) Julian Alps, and 6) Carnia (natural passage north to south). Their idiosyncrasies result in visitor flows towards hotspots

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and require comprehensive strategies at the sub-regional level. For this reason, the present paper proposes DTW with HCA due to its superiority compared with alternative methods applied to short time series. Most important, commonly used attempts cannot identify similar seasonality patterns that are out of phase. The five municipality groups derived from the proposed approach match to a large extent with pre-defined tourism regions [19] validating the results. The analysis of the mobile phone time series data clearly shows that the hotspots are positioned in the cluster with the highest seasonality effects (cluster 1), which indicates that visitors include these hotspots in their itineraries while they are in the region. Cluster 2 being mainly located in the Julian Alps is famous for hiking and skiing. In this respect, cluster 4 shows potential for disentangling the concentration of tourists from the surrounding areas. Results help DMOs to identify intra- and inter-regional strategies to better distribute tourist flows during seasonal peaks.

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Climate Change and Artificial Intelligence.
A text analysis on academic and grey literature

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Abstract. This study investigates the intersection of Artificial Intelligence (AI), climate change, and tourism through a comprehensive text analysis of academic and grey literature in English and Italian. Using the Scopus database and Google searches, we collected 58 multi-type sources and analyzed them with AntConc, a corpus analysis toolkit. Our findings reveal a predominant focus on AI and machine learning technologies for climate change mitigation rather than adaptation. Data emerges as a central theme across all literature types, underscoring the data-driven nature of both AI applications and climate research. Machine learning, deep learning, and neural networks are prominent in academic literature, while grey literature emphasizes greenhouse gas emissions and environmental impacts. The Italian grey literature uniquely highlights risks and sustainability. This research identifies the potential of AI in addressing climate change challenges in tourism while also highlights the need for more studies on adaptation strategies and consideration of AI's own environmental impact.

Keywords: Tourism, Climate change, Artificial Intelligence, Mitigation, Adaptation.

1   Introduction

Two factors are shaping, and will influence strongly in the future, the tourism phenomenon and its components: artificial intelligence and climate change. Even in apparently belonging to different realms, the connection between them is well established [1].

As artificial intelligence (AI) becomes increasingly embedded into our daily lives, much attention is focused on the potential ethical issues that concern privacy, security. Beyond these important issues, however, AI holds a remarkable potential to optimize various activities, boost efficiency, and significantly improve the accuracy and effectiveness of systems that rely heavily on predictions and probabilities. Most promising applications, in fact, lie in areas that address complex technical challenges that exceed human capacity. One such challenge is climate

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change, a multifaceted problem that demands significant transformations across key sectors, including transportation, agriculture, construction, and energy [1].

AI has the potential to play a critical role in tackling climate change, with the energy sector providing a prime example of its promise and limitations. Through AI, we can optimize energy usage, predict consumption patterns, and integrate renewable sources more effectively into power grids. However, this technological shift also introduces important policy trade-offs. To truly benefit from AI's potential in combating climate change, we must approach its use thoughtfully, balancing its strengths with its risks and ensuring it is applied in ways that minimize drawbacks while maximizing its ability to reduce greenhouse gas emissions.

Some tourism destinations – especially in Northern Europe – are already using adaptive policies often based on AI technologies. It is clear that Artificial Intelligence may be an innovative instrument to prevent and manage climate change in tourism, but might also cause an increase in energy consumption which may affect the state of the planet [2]. An example of a Northern European destination which is using an Artificial Intelligence tool to implement climate adaptive policies is given by Visit Norway – the Norwegian DMO – who on their website published a CO2 calculator [2].

This is one of the possible examples on how AI tools can help in facing climate change in the tourism industry. Another increasingly important role of AI in the contrast of climate change is the use of data to forecast the emergence of climate extremes (e.g.: increase in heat days, droughts and floods, sea level rise, etc.) which can have a wide impact on all the tourism products. Forecasting gives to destinations the opportunity to implement adaptive policies in advance, instead that following the emergencies.

As part of a larger ongoing project on the attitudes of Italian tourism destinations towards the issues of climate change, we performed an investigation on how these topics are discussed in three types of literature: academic literature in English language, grey literature in English, and grey literature in Italian. Here we report a preliminary analysis of this exploration as the results might be relevant for those interested in these issues and pose some questions that concern the similarities and the differences between these three different sources.

2   Materials and methods

2.1   Data collection

The academic literature paper were collected by using the Scopus database. First of all we searched for papers which had in the title and in the abstract the keywords "artificial intelligence", "climate change" and "tourism". The result of these first research is a spreadsheet of 4.076 titles and abstracts. Then by reading this first output we selected a list of 90 papers with a clear focus on artificial intelligence, climate change and tourism. At a later stage to reduce our field of research from this list of 90 papers we selected 15 papers which discuss about Artificial Intelligence, climate change and tourism together. We also selected the most recent (2020-2024) and most cited publications for providing a relevant and updated view.

For what concerns the grey literature data have been collected by running a set of 30 keywords both in English and Italian on Google.com and by selecting articles related to our three topics from online newspapers, magazines, institutional websites (i.e. NASA, European Parliament, World Economic Forum, etc.), private companies (i.e. Boston Consulting Group, McKinsey, etc.), research institutes (i.e. Climate Change AI, Centre for AI and Climate, etc.). Thanks to this process we managed to get 32 contributions in English and 11 in Italian.

In the end, adding up all the different paper and articles, we scrutinized 58 multi-type sources.

2.2   Data treatment and analysis

All the texts from pdf and website pages have been copied into three different notepads: one for academic literature, one for English grey literature and another one for Italian grey literature.

Then all the notepads have been run separately with AntConc [4], a freeware corpus analysis toolkit for text analysis based on Python, being careful of using proper stopwords in Italian and English to reduce possible biases.

With AntConc we were able to analyze word frequencies and N-grams frequencies (bi-grams), obtaining in this way six tables (three words tables and three N-grams tables) which give us the point of view of our three main sources on which are the main concepts connected to Artificial Intelligence, climate change and tourism and show us which are the

main similarities and differences between the academic literature, the grey literature in English and in Italian.

3   Results

In tables 1, 2 and 3 it is visible how the main topics discussed in all the three literatures considered are connected to how Artificial Intelligence and machine learning technologies can prevent climate change effects [5]. In general we can say that the main focus is on mitigation solutions and not on adaptation.

Table 1. Top 5 N-grams in English academic literature

Rank	N-gram	Frequency
1	Machine learning	557
2	Deep learning	202
3	Neural networks	184
4	Data driven	117
5	GHG emissions	97

Table 2. Top 5 N-grams in English gray literature

Rank	N-gram	Frequency
1	Machine learning	62
2	Greenhouse gas	8
3	Satellite imagery	8

As stated by the European Environment Agency (EEA) "mitigation" means making the impacts of climate change less severe by preventing or decreasing the emission of greenhouse gases (GHGs) into the atmosphere. Mitigation is achieved by reducing the sources of these gases or by enhancing their storage. In short, mitigation is a human intervention that reduces the sources of greenhouse gas emissions and/or strengthens sinks. In contrast, the term "adaptation" denotes the anticipation of the harmful consequences of climate change and the implementation of suitable strategies to prevent or mitigate the potential damage, while simultaneously exploiting the potential opportunities that may emerge. In essence, adaptation can be understood as the process of adjusting to the current and future effects of climate change [6].

The fact that the main focus is on mitigation and possible uses of technology to prevent or reduce climate gas emissions is also visible in the

top 5 words in every literature (table 4, 5 and 6). Another evidence based on the word analysis is the centrality of data in both fields of Climate Change and Artificial Intelligence [7].

Table 3. Top 5 N-grams in Italian gray literature

Rank	N-gram	Frequency
1	Gas serra (GHGs)	16
2	Impatto ambientale (Environmental impact)	12
3	Riscaldamento globale (Global warming)	11
4	Consumo energetico (Energy consumption)	9

Table 4. Top 5 words in English academic literature

Rank	Word	Frequency
1	Data	1.708
2	Learning	1.007
3	Energy	952
4	Models	844
5	Machine	636

Table 5. Top 5 words in English gray literature

Rank	Word	Frequency
1	Data	84
2	Learning	66
3	Machine	64
4	Energy	52
5	Carbon	40

Table 6. Top 5 N-grams in Italian gray literature

Rank	Word	Frequency
1	Rischi (risks)	49
2	Dati (data)	48
3	Impatto (impact)	44
4	Sostenibilità (sustainability)	44
5	Emissioni (emissions)	38

4   Conclusions

This study analyzed the intersection of Artificial Intelligence (AI), climate change, and tourism across academic and grey literature in both English and Italian. Our analysis reveals several key findings:

1. There is a strong focus on how AI and machine learning technologies can mitigate climate change effects, rather than on adaptation strategies [8.9].
2. The importance of having a good set of data is evident across all literature types, highlighting the data-driven nature of both AI applications and climate change research.
3. Machine learning, deep learning, and neural networks emerge as dominant topics in the academic literature, indicating their significance in climate change-related research [10].
4. Both English and Italian grey literature emphasize GHGs emissions and environmental impacts, suggesting a consistent concern across different cultural contexts [11,12].

These findings underscore the potential of AI in addressing climate change challenges, particularly in the tourism sector. However, they also point to a need for more research on adaptation strategies and a broader consideration of AI's own environmental impacts. In fact, most of the literature examined deals with mitigation actions while adaptation strategies or policies are relatively overlooked.

We came to this conclusion because most of the top 5 words and bi-grams published in tables, both in English and Italian, and in academic and grey literature, are clearly focused on mitigation policies. Summarizing all the analyses, we can state that one cluster of words and bi-grams refers to methods and technologies (e.g.: machine learning, deep learning, data, etc.) that are already applied in the implementation of mitigation policies in most economic sectors. The other cluster consists of words and bi-grams directly related to mitigation policies (GHG emissions, greenhouse gas, gas serra, energy consumption, etc.). This is also in line with the definition of the differences between adaptation and mitigation given by the European Environment Agency: while the former means anticipating the adverse effects of climate change, the latter means making the effects of climate change less severe by preventing or reducing the emission of greenhouse gases (GHG) into the atmosphere.

Future work should aim at bridging the gap between academic research and practical applications, ensuring that AI technologies are leveraged effectively and responsibly in the fight against climate change and to support the definition of new adaptive strategies. By fostering collaboration between researchers, policymakers, and industry leaders, the power of AI can be used in more efficient and effective way to build a more sustainable and resilient future.

Acknowledgments

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Exploring the Role of Generative AI for Economic Sustainability in Rural Tourism: A Comparative Study of Andorra and La Terra Alta

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Abstract. This study explores how Generative AI (GenAI) can address digital exclusion and support rural tourism in La Terra Alta, using Andorra as a contrasting case. Andorra is experiencing population growth and high housing costs, while La Terra Alta faces depopulation, highlighting disparities in economic sustainability. Using a complex systems approach, we examine behaviors across eleven dimensions, including technology adoption, skills, and infrastructure. This research aims to foster economic resilience and provide recommendations for regional development. Preliminary findings suggest that while Andorra's advanced infrastructure supports generative innovation, Terra Alta requires foundational investment to reach similar benefits. The results offer practical insights for policymakers and stakeholders on designing inclusion strategies for sustainable growth. Findings are expected to guide policies to balance economic opportunities and improve quality of life in rural areas, ensuring growing and declining regions benefit from GenAI.

Keywords: Generative AI, Sustainable Business model, Rural Tourism, Economic Sustainability.

1 Introduction

Rural tourism has grown worldwide, driven by the increasing interest in sustainable travel and unique cultural experiences. Globally, rural tourism is growing at around 6% annually, a figure comparable to the overall tourism sector, which grows at approximately 4-5% per year, according to the UNWTO. This rise has been propelled by travelers seeking more authentic, eco-friendly experiences outside crowded cityscapes [1]. In Spain, rural tourism has emerged as a significant sector within the national tourism economy. This rise highlights the growing preference for rural destinations as alternatives to traditional tourist

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spots, driven by increased demand for open and less crowded areas following the COVID-19 pandemic [1].

In rural areas, digital exclusion remains a critical issue, especially regarding advanced technologies like GenAI. Digital exclusion affects the competitiveness of rural businesses, limiting their ability to adopt digital tools that improve efficiency, customer engagement, and sustainability [2]. Addressing economic sustainability in rural areas is key to preventing depopulation. By offering new business opportunities and increasing efficiency, GenAI can help make rural regions more attractive, supporting population retention and overall economic growth [3]. GenAI can enhance rural tourism through digital marketing, personalized content, demand forecasting, yield management, and education. It can automate services like customer support, bookings, and virtual tours, reducing costs and increasing efficiency. GenAI also helps businesses learn new skills for competitive advantage, providing training and educational resources to upskill the workforce.

1.1 Purpose of this research

GenAI offers competitive opportunities for rural tourism by aligning with local economic and social institutions. By leveraging regional innovation ecosystems, GenAI can foster economic sustainability. This research uses a complex systems approach to understand how rural tourism firms adapt and innovate within their ecosystem. We compare Andorra and La Terra Alta to determine how overcoming digital exclusion and promoting GenAI can improve economic sustainability.

GenAI can transform rural areas if its unique regional characteristics are integrated into policy and practice.

Consequently, this research proposes the following question: To what extent can overcoming digital exclusion and promoting the use of Generative AI by rural tourism businesses improve their economic sustainability and, in turn, the economic sustainability of the entire region? We argue that GenAI can act as a transformative force in rural areas, provided that the unique characteristics of each region are considered and properly integrated into policy and practice.

This study focuses on Andorra and La Terra Alta, so findings may not be fully generalizable to all rural areas. However, the lessons learned provide valuable insights into GenAI adoption, offering a foundation

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for further research. New insights from this work should help understand how GenAI contributes to economic sustainability in rural areas. Government agencies and regional stakeholders can use these findings to design better policies for promoting GenAI in rural tourism.

Case 1: Andorra, a small Pyrenean nation, relies on tourism—mainly winter sports and shopping—for about 55% of its GDP [11]. Attracting millions with its tax-free status and ski resorts, Andorra now faces challenges from shorter snow seasons due to climate change [12]. To address this, it is promoting rural tourism to spread economic benefits to mountain communities, indicating a shift toward sustainability, though specific rural tourism data remains scarce [13].

Case 2: La Terra Alta, a Catalan region known for its wine and Spanish Civil War sites, has seen steady growth in rural tourism, particularly in wine tourism, which supports the local economy [14,15]. Despite demographic decline and infrastructure challenges, its cultural heritage and natural beauty make it a model for sustainable rural tourism that appeals to niche markets [16].

2 Literature Review

This literature review integrates Dynamic Capabilities, Institutional Theory, Regional Development, and Complexity Theory to create a cohesive framework for understanding Generative AI (GenAI) in rural tourism. Each theory contributes a unique perspective that, when combined, provides a comprehensive view of how GenAI can impact rural tourism businesses and their broader ecosystems. Additionally, the definitive design of the conceptual framework will borrow descriptive insights from the Theory of Complexity and Complex Adaptive Systems to build the complex system.

Dynamic Capabilities emphasizes the ability of rural tourism firms to adapt, innovate, and absorb new technologies like GenAI. By fostering these capabilities, rural businesses can better respond to market shifts, integrate GenAI into their operations, and enhance their resilience and competitiveness, particularly in contexts with limited infrastructure and skills. In this vein, the Dynamic capabilities frame uses a three-pronged framework: Technology Acceptance Model (TAM) [7] to identify perceived usefulness and ease of use as critical factors for technology adoption, Resource-Based View (RBV) [8] as in rural tourism, digital skills and infrastructure are critical resources that influence GenAI

adoption and help firms respond to market changes [4], and Innovation Diffusion Theory (IDT) [9], understanding the spread of GenAI helps explain why some areas, such as Andorra, might adopt these innovations more quickly than regions like Terra Alta.

Institutional Theory [5] helps us understand the external forces shaping the digital landscape for rural tourism, including government policies, regional support systems, and collaborations. Institutional support is crucial for promoting digital inclusion and incentivizing GenAI adoption, which in turn facilitates the integration of advanced technologies in rural firms.

Regional Development Theory [6] provides insights into the socio-economic evolution of rural areas, driven by local actors and innovation. The interaction between rural tourism firms, local institutions, and regional systems is key for understanding how GenAI can foster sustainable economic growth. These dynamics create a foundation for regions to harness technological innovation, promoting both survival and growth.

Complexity Theory [10] ties all these elements together by viewing rural tourism as part of a complex adaptive system. Rural businesses, institutions, and regional actors interact in ways that often lead to unpredictable outcomes. GenAI serves as a catalyst in this system, driving both incremental improvements (adaptive behaviors) and transformative changes (generative behaviors). Understanding GenAI through this lens helps illustrate how small shifts, such as improved skills or better institutional support, can significantly impact the rural tourism ecosystem.

This integrated approach highlights both opportunities and challenges faced by rural tourism businesses in adopting GenAI, and underscores the importance of institutional and regional support in achieving successful technology adoption.

3   Methodology

This research employs a comparative case study methodology to analyze Andorra and La Terra Alta, regions chosen for their contrasting digital environments. The comparative approach enables us to examine how different contexts influence the adoption of GenAI, with Andorra representing a region with advanced digital infrastructure, while La

Terra Alta has more limited capabilities. This contrast allows for an in-depth understanding of the varied factors that drive or inhibit GenAI adoption.

To provide a comprehensive view of the rural tourism ecosystem, the study uses purposive sampling to select participants who can offer insights into the adoption of GenAI. Specifically, semi-structured interviews will be conducted with representatives from tourism promotion institutions, members of the chambers of commerce, and rural tourism business owners in both Andorra and La Terra Alta. These participants were selected because they represent key actors in the tourism value chain, and their perspectives are crucial for understanding the systemic challenges and opportunities associated with GenAI adoption in rural areas.

The semi-structured interviews will focus on understanding participants' experiences, the perceived benefits, and the challenges of integrating GenAI into rural tourism. Questions cover topics such as digital infrastructure, skill levels, institutional support, and current uses or intentions regarding GenAI, along with the eleven dimentions identified in the theoretical framework:

1. **Digital Infrastructure:** Based on TAM, this dimension assesses the quality of connectivity, which influences ease of GenAI adoption [7].
2. **Digital Skills of Workers:** Linked to RBV, it evaluates skills as a resource for competitiveness [8].
3. **Adoption of Digital Tools:** Assessed through TAM for readiness in integrating GenAI [7].
4. **Institutional Support for Digitization:** Under Institutional Theory, this dimension evaluates external support for digital transformation [5].
5. **Technological Innovation (non-GenAI):** Using Dynamic Capabilities, this dimension considers innovation readiness [4].
6. **Public-Private Collaboration:** Based on Institutional Theory, it assesses collaborative efforts [5].
7. **Absorptive Capacity for GenAI:** Linked to Dynamic Capabilities, focusing on the ability to apply new knowledge [4].
8. **Innovation Driven by GenAI:** Related to Innovation Diffusion Theory, examining AI's impact [9].
9. **Skills for GenAI:** Under RBV, assessing skill readiness for AI adoption [8].

10. **GenAI Infrastructure:** Using TAM, evaluating system adequacy for AI [7].
11. **Institutional Support for GenAI:** Under Institutional Theory, examining initiatives for AI adoption [5].

In addition to the interviews, document analysis is conducted to enrich and triangulate the findings. Data sources include materials from tourism institutions, official websites of the chambers of commerce, local government reports, news articles, and existing case studies. This analysis helps contextualize the findings from the interviews by providing additional insights into the digital environment, institutional support, and regional strategies for tourism and technology adoption.

The data collected from interviews and documents is analyzed using thematic analysis. This method allows us to identify recurring themes related to digital exclusion, economic sustainability, and the potential role of GenAI in enhancing competitiveness in rural tourism. By coding and categorizing data across different stakeholder groups and data sources, we aim to provide a nuanced understanding of the dynamics influencing GenAI adoption in each region and its influence in regional development.

Our research is applying a qualitative approach that combines primary data from in-depth interviews with secondary data from document analysis, ensuring a more reliable and comprehensive understanding of the factors affecting GenAI adoption. By integrating perspectives from multiple stakeholders and data sources, this research aims to generate actionable insights for promoting economic sustainability in rural tourism through the strategic use of GenAI.

4   Preliminary Findings

The interview process and the analysis of archival documentation are still underway, and as of this working paper submission, no definitive findings are available. However, based on early data collection and the emerging themes from initial stakeholder discussions, we anticipate gaining several preliminary insights that are indicative of broader trends.

Preliminary findings suggest that the adoption of Generative AI (GenAI) in rural tourism is heavily influenced by both the availability of digital infrastructure and the level of institutional support. In Andorra, where infrastructure is relatively advanced, stakeholders report

greater openness and readiness to implement GenAI solutions for enhancing marketing, customer engagement, and operational efficiency. Early discussions indicate that tourism businesses are particularly interested in leveraging GenAI for improving yield management through more accurate demand forecasting and for enhancing visitor experiences via personalized digital interactions. A proof of this is the numerous courses offered by both the Andorran Chamber of Commerce and the Government of Andorra on artificial intelligence applied to tourism. In contrast, stakeholders in La Terra Alta highlight significant challenges related to insufficient digital infrastructure and limited digital skills, which hinder the adoption of GenAI. Initial feedback points to a critical need for targeted investments in digital literacy programs and better connectivity. Moreover, institutional support in La Terra Alta appears fragmented, with stakeholders expressing uncertainty about accessing the resources necessary to implement GenAI effectively. Despite these challenges, there is a growing recognition of the potential for GenAI to reduce operational costs and expand market reach if foundational issues are addressed.

A recurring theme from both regions is the importance of collaboration across stakeholders—including tourism businesses, local governments, and chambers of commerce—to facilitate GenAI adoption. In Andorra, such collaborations seem more advanced, resulting in a more favorable environment for innovation. In La Terra Alta, these networks are less established, suggesting that strengthening collaborative frameworks could play a key role in fostering technology adoption

5 Conclusion

This research underscores the potential of Generative AI (GenAI) to reduce digital exclusion and enhance economic sustainability in rural tourism. Through a comparative analysis of Andorra and La Terra Alta, our preliminary insights point towards several key factors that influence GenAI adoption: digital infrastructure, institutional support, stakeholder collaboration, and workforce digital skills.

For practical implementation, the findings suggest that policy interventions should be tailored to the specific needs of each region. In Andorra, further optimizing existing infrastructure and continuing to foster collaboration among stakeholders will likely accelerate GenAI adoption. For La Terra Alta, targeted investments in digital infrastructure,

such as the deployment of fiber optic throughout the territory, comprehensive digital literacy programs, and enhanced institutional support are critical prerequisites for unlocking the potential benefits of GenAI. These insights are valuable not only for academic research but also for policymakers and practitioners looking to leverage digital technologies in rural contexts. By understanding the specific conditions that facilitate or hinder GenAI adoption, stakeholders can design more effective interventions to promote sustainable economic growth in rural areas. Future research should extend this comparative analysis to additional rural regions to deepen the understanding of digital exclusion and to identify broader patterns that can inform policy and practice in diverse rural settings.

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AI Extended travel images and intention to share

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Abstract. Although AI-extended images are considered effective in improving the travel images' aesthetic quality, it remains unclear how they can improve images' aesthetic quality and their subsequent impacts of AI-extended images on tourists' behavioral outcomes. Based on Birkhoff's theory and through one field study and one online experiment, the results of this research indicated that AI-extended image contributes significantly to increasing the aesthetic quality of travel images by increasing the order and complexity of images simultaneously, further enhancing the ratio of order and complexity. The results of online experiment revealed that AI-extended images were positively related to tourists sharing intention. This study contributes to the information technology literature in tourism by offering a new perspective into the GenAI image-to-image phenomena.

Keywords: Extended Travel Images, Image Analytics, GenAI Images.

1 Introduction

Aesthetic experiences, initially proposed in the realm of art, involve cognitive processes where individuals engage with aesthetic stimuli through classification, interpretation, and engagement (Leder et al., 2004), has been extended to tourism, such as the appreciation of nature (Trinh & Ryan, 2016). As a prevalent practice, travel image serves not only as a form of artistic expression but also as a means for tourists to amplify the aesthetic value of their memories for social media sharing (Pan et al., 2014). The recent advent of Generative Artificial Intelligence (GenAI) has revolutionized image aesthetics in tourism. AI-extended images, as a typical example, have gained increasing popularity in TikTok, allowing tourists to enrich their original tourism photos by adding or refining elements, such as inserting ships on rivers or birds in the sky, thereby increasing the aesthetic of the images (see Fig. 1). In the context of TikTok/Douyin, AI extension often involves the

automatic enhancement of image features such as lighting and texture, and the creative addition of elements like wildlife or architectural features. These platforms use consistent algorithms to ensure that enhancements improve the overall aesthetic quality by balancing the increased complexity with symmetrical order. This study examines such consistent changes and their impact on viewer perception and sharing intent. To clarify, by AI extension, we refer to the process of enhancing digital images using Generative AI technologies that alter or add elements to the original composition. This includes object insertion and scene modification. While previous studies have examined the aesthetic quality of text-generated images (Göring et al., 2023), how image-to-image transformation influence the image aesthetic quality and tourists' sharing intention remains unexplored. Thus, this study aims to examine the aesthetic quality of AI-extended images and its impact on tourists sharing intention through image analytics and online experiment.
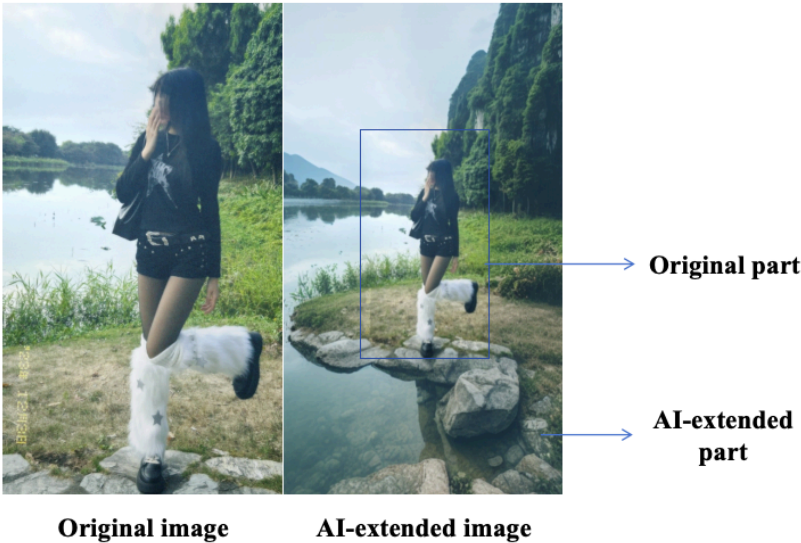
Fig. 6. A typical example of an AI-extended image

2   Literature Review

2.1   Birkhoff's Theory of Aesthetics

Birkhoff's (1933) theory of aesthetics suggests that an image's beauty is derived from its order-to-complexity ratio, which enhances its aesthetic quality as the ratio improves. This concept underpins computational aesthetics by measuring image order and complexity. For instance, various methods have been employed, such as algorithmic self-similarity (Redies et al., 2012; Braun et al., 2013), mirror or radial symmetry (Bies et al., 2016; Kumar et al., 2024) to assess order, while complexity has been measured using Pyramid of Histograms of Orientation Gradients (PHOG) complexity (Braun et al., 2013) or the sum of the strengths of all oriented gradients (Bies et al., 2016; Kumar et al., 2024).

2.2   Generative AI (GenAI) Images

Generative artificial intelligence (GenAI), as computational methods that produce seemingly novel, meaningful content such as text, images, or audio from existing data, has revolutionized the traditional ways that only humans can perform creative and artistic tasks (Feuerriegel et al., 2024. p.111). By generating new content indistinguishable from that created by human skill, GenAI has transformed professional practices and communication methods (Susarla et al., 2023). Unlike traditional photo editing tools such as Photoshop, which primarily adjust existing elements within a photograph, AI enhancements can introduce entirely new components into the scene, thereby altering the image more fundamentally. The significant advancements in deep learning alongside the availability of extensive datasets have facilitated this evolution, with innovations like StyleGAN and OpenAI's GPT (Karras et al., 2019; Bandi et al., 2023).

In tourism, GenAI has been acknowledged for their ability to reduce costs and save time (Wang, 2024) while increasing productivity and efficiency (Carvalho & Ivanov, 2024). The recent advent of AI-extended images on Chinese social media platforms marks a significant development. This new GenAI application enhances images by adding elements or completing parts of initially incomplete images, leading to improved visual appeal and atmosphere. This feature has been especially

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effective in enhancing landscape images, garnering significant user acclaim for its ability to beautify and add atmospheric depth.

3 Hypotheses Development

3.1 Complexity, Order and Aesthetic Quality

Building on Birkhoff's (1933) theory, aesthetic quality can be evaluated through a ratio of order to complexity, positing that higher values correlate with increased aesthetic quality (Rigau et al., 2007). In our study, we examine the use of AI-extended images, which enhance images by adding elements or completing parts. This process increases the images' complexity while maintaining visual symmetry. We propose:

> H1: AI-extended image increases the aesthetic quality of travel images by raising the value of complexity and order, and the ratio of order and complexity.

3.2 Sharing Intention

Birkhoff's theory (1933) suggests that aesthetic experiences begin with the viewer's focused attention, crucial for both action and perception. This is particularly relevant in visual aesthetics, where more complex images, characterized by their variety and numerosity, demand greater conscious attention, thus enhancing the perceived value (Kumar et al., 2024). Both complexity and order contribute to perceived aesthetic quality, which are relevant to sharing intentions (Kolekofski Jr & Heminger, 2003). Thus, AI-extended images, which typically exhibit increased complexity and order, are likely to enhance tourists' sharing intention due to their high aesthetic quality. We propose:

> H2: AI-extended images will have a stronger influence on sharing intention than original images.

4 Image Analytics

Our study utilized field data from Chinese TikTok Platform (Douyin), where users and influencers share both original and AI-extended travel images. We collected 782 pairs of travel images, each consisting of an

original and an AI-extended version. Analysis was conducted using the *imagefluency* package in R (Mayer, 2021), which excels in statistical and predictive capabilities, providing interpretable results and handling direct color image processing. We measured the average symmetry (order) and complexity for both original images and AI-extended images, and then divided them into two groups. Finally, one-way ANOVA was used to test hypothesis 1.

The results revealed significant differences between original and AI-extended images in terms of order (Moriginal=0.355, MAI-extended=0.408, F(1,1562)=26.783, P<0.001) and complexity (Moriginal=0.408, MAI-extended=0.433, F(1,1562)=13.157, P<0.001). These findings indicate that AI-extended images enhance both the order and complexity of images, thus improving their aesthetic quality, supporting hypotheses 1.

5   Online experiment

In our experiment, participants compared an original travel image with its AI-extended version using a within-subjects design. We recruited 200 individuals excluding 20 for failing attention checks, leaving 180 participants (31.1% male, average age 29.43, SD=7.916). Each participant was shown a pair of images. Subsequently, participants responded to a survey on sharing intentions, based on a scale from Reychav and Weisberg (2010) ranging from 1 (strongly disagree) to 7 (strongly agree), and answered five demographic questions including age, gender, educational background, monthly income, and occupation. A paired samples T-Test was used to examine whether AI-extended images influence sharing intention.

The results showed that mean values of sharing intention for original images was 4.928, compared to 5.347 for AI-extended images, with a significant difference in sharing intention (t (179) =2.675, p=0.008, d=0.199, 95% CI [0.110, 0.729]), supporting hypothesis 2.

6   Conclusion and Implications

This study explores the impact of AI-extended images on the aesthetic quality of travel images and their influence on tourists' sharing intention guided by Birkhoff's theory. The study employed image analytics and an online experiment to investigate these effects. Findings from the

image analysis indicate that GenAI tools improve the aesthetic quality of images by enhancing order values, complexity values, and their ratios. Additionally, evidence suggests that these enhancements in aesthetic quality, derived from the balance of order and complexity, positively influenced tourists' sharing intention.

This study advances theoretical knowledge in information technology literature in tourism. First, it innovatively considers the aesthetic quality of images as a novel antecedent and examines its effect on tourists' sharing intention. Additionally, it enriches Birkhoff's theory by exploring AI-extended images and the implications of aesthetic quality enhancements. Second, the study addresses the call for a deeper understanding of GenAI (Wang, 2024) by exploring both the antecedents and effects of tourism-specific GenAI (Hsu et al., 2024). Practically, the findings offer significant insights for Destination Management Organizations (DMOs). DMOs can collaborate with social media platforms to create destination-specific GenAI tools, offering tourists innovative ways to enhance the aesthetic quality of their travel images and boost tourists' sharing intention.

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Green Goals, Digital Tools: How AI and eWOM Can Drive Sustainable Hospitality

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Abstract. Sustainability is a worldwide trend in the hospitality industry. To facilitate sustainable behavior, it is necessary to understand how it relates to customer satisfaction, how sustainability communication affects customer awareness, and eventually how it translates into a return on investment for hospitality decision-makers. Previous research does not consider how eWOM (electronic word-of-mouth) may serve as a data source for influencing sustainable behavior within the hospitality industry. This study explores how AI can leverage online reviews to understand customer perceptions of sustainability in hotels. By analyzing customer sentiment and awareness, we aim to identify strategies that encourage sustainable behavior and improve ROI for hospitality businesses.

1   Introduction and Literature Review

Green practices' definition in the hospitality industry varies. Kim, Lee & Fairhurst [16] defined green practices as "a value-added business strategy that benefits a hospitality operation that engages in environmental protection initiatives". Similarly, Rahman, Reynolds & Svaren [29] defined "green" as "environmentally friendly, that is doing business in a way that reduces waste, conserves energy, and generally promotes environmental health". Myung, McClaren & Li [26] stated that green practices aim to reduce the negative impact on the environment by adopting environmental measures for reducing waste and using sustainable materials and resources [1].
Green practices have been evolving for decades in the hospitality industry, gaining substantial momentum in the 1990s [5] and continuing to grow in importance and significance [27]. Thanks to continuous attention from practitioners [24] the subject of green practices has become a

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research topic of interest in the hospitality literature. Eventually, in order to be economically valuable, green initiatives have to reduce operational cost and create perceived value for costumers [30]. Numerous studies explore the role of hotel green practices in determining guest behavioral intentions [8], showing that hotel commitment towards sustainability is a significant determinant of guest satisfaction [7] [20]. Rogerson & Sims [31] considered that hotels which implement sustainable practices are more competitive because customers expect to find environmental attributes.

The implementation of green practices in the hospitality industry varies based on internal organizational factors, such as financial strength and managerial attitudes [22], and external business variables, such as stakeholder pressure and environmental regulations [18]. However, and although the benefits derived from addressing sustainable practices are clear in terms of costs reduction, enhanced customer satisfaction, trust and improved benefits [3] [6], many hospitality managers still focus on maximizing profits and controlling costs while ignoring the potential of sustainability [14]. All the more so since, as service firms encounter unique challenges when attempting to incorporate green practices into their service design, such practices may arguably undercut customer demand and undermine a customer's sense of indulgence [19]. As such, some hotels may hesitate to implement green practices for fear that they could lead to customer inconvenience and diminish customer satisfaction [10].

On the demand side, it has been pointed out that a deeper understanding of the sustainable behavior of tourists is required [12]. In the consumer behavior literature, environmentally-sustainable behaviors are frequently described as green consumption activities [4] [15] [11]. Specific pro-environmental behaviors, such as water saving, recycling, energy saving, public transportation use, avoidance of disposable product use, or environmental protection [25] [28] [35] are explained within a conceptual framework [21] provided by reasoned action theory and the theory of planned behavior [2]. Predictors of green customer satisfaction in hospitality services can be characterized as threefold: first-order predictor is the existence of such green practices within the industry, second and third order predictors being whether said green practice directly affects and whether it is observable by the guest [9].

According to stakeholder theory, customers constitute one of the most salient stakeholder groups. Customers evaluate the service experience

based on interactions with a firm during the consumption stage [10]. Thus, customers' actual experiences with green practices should have a significant impact on their overall assessments of service consumption. Only a few studies focusing on customer satisfaction and sustainability have considered user-generated content as a data source for investigating the relationship between sustainability and customer satisfaction in hospitality [9]. User-generated content (UGC) refers to the sharing of information among tourists via online reviews. Also known as 'eWOM', it encompasses "any positive or negative feedback provided by potential, current, or past consumers" outside the conventional buyer-seller relationship (Hennig-Thurau et al., 2004). eWOM is publicly available via the internet, specifically on online travel agencies (OTAs) such as Booking.com, on the websites of destination management organizations (DMOs), and of course on the websites of hotels. eWOM provides an abundant data source [32], and offers ways to analyze, interpret and manage the influence consumers may have on one another [17] [34].

Conversely, although managerial response strategies to eWOM is being increasingly discussed, it mostly consists in analyzing webcare strategies, that is the act of participating in online conversation with consumers and to respond to consumer review. There is on the other hand a paucity of literature on managerial responses to eWOM in terms of green service offering as well as sustainability communication, be it online or offline [33] [32].

Fig. 1. Categorizing green efforts for user-generated content (U.G.C.) analysis.

The aim of this research is to address this gap, by analyzing how user-generated content may influence managerial strategies towards green practices and sustainability communication. As depicted in Figure 1, the actual existence of hotel green practices, whether or not they impact the guest experience, and whether or not they are observable by guests, are liable to influence customer evaluation [9]. This research employs a methodology that analyzes UGC generated by hotel guests, extracts components related to the hotel's green practices, and assesses the sentiment expressed regarding the identified green practices. Thus, we aim at addressing the following research questions :

RQ1 : does user-generated content (U.G.C.) include references to hotel's green practices, or lack thereof?
RQ2 : Is UGC more likely to include reference to green practices if they directly affect the guest?
RQ3 : Is UGC more likely to include reference to green practices if they are observable by guest?
RQ4 : If UGC contains such references, does the user express a sentiment associated with the reference?

The ambition of this ongoing research is to provide recommendations to managers, encouraging them to recognize the ROI of sustainability efforts by highlighting evidence of customer recognition and showcasing success stories from other hotels, and to define effective sustainability communication strategies.

2   Methodology

2.1   U.G.C. Processing and Interpretation Methodology

The study focuses on the 100 hotels registered with the Marseille tourist office (Southern France). A total of 87,222 guest reviews were scraped from Google, TripAdvisor, Booking.com, and hotel websites, covering a period from January 1st, 2022, to August 31st, 2024. Before analyzing the reviews for their green content, they undergo a series of preliminary operations. First, reviews are broken down into sentences, called "fragments," using a text-to-sentence splitter module .

These fragments are then converted into tokens, which are essentially character strings, word combinations, and punctuation marks.

Two classification models have been trained. The first model classifies fragments into sustainable development themes, while the second model assigns a positive, negative, or neutral sentiment to each fragment. Both models were trained using supervised learning. Supervised learning involves training a model to classify fragments based on similarity. This is achieved by extracting sentences and assigning them a class, such as "biodiversity." The model learns the semantics and similarities associated with this class. Once training is complete, the model is presented with a new, unseen fragment: it calculates the similarity of this new fragment to those it encountered during training and returns a probability of the new fragment belonging to the class (e.g., biodiversity) or not. In essence, the goal is for the model to make predictions on new data that are similar to the data it was trained on.

The first model was trained to determine whether a fragment belongs to a theme or not. To define the sustainable development themes used by this model, criteria from the main European and Global environmental tourism labels (Green Key, Green Globe, EU Ecolabel) were aggregated into eight themes (biodiversity, waste, water, circular economy, CO_2, energy, mobility, corporate social responsibility, accessibility) and 40 sub-themes. When presented with a new fragment, the model predicts and classifies it into one of the eight themes.

The second model was trained to determine whether these fragments were positive, neutral, or negative. The resulting sentiment is specific to a fragment and is associated with a theme and sub-themes. For example, consider the following guest review: "Thank you for turning on the terrace heating when it started to get cold during the meal." While the wording appears positive, implying satisfaction with the hotel's decision, the model classifies this fragment as negative because outdoor heating is considered wasteful energy use.

To compare green content across hotels or observe changes within a hotel over time, a weighting algorithm is implemented to assign quantitative scores. Each fragment categorized into a theme receives a certain number of points based on its associated sentiment (positive, negative, neutral). The algorithm for calculating points for themes and sub-themes is scalable and integrates various criteria, such as the presence of labels or the number of occurrences of a predicted theme.

2.2 Interpretation of customer feedback through AI and support for hoteliers in adapting their green practices and sustainability communication.

(This project component is under development.)

We are organizing regular workshops with Marseille hoteliers to analyze AI-generated insights from customer reviews. Our primary goals are to:

1. Gap Analysis: Compare actual green practices with customer perceptions.
2. Communication Strategy: Recommend sustainability communication improvements based on customer feedback and competitor analysis.
3. ROI Focus: Identify practices - green practices, sustainability communication - that yield the highest return on investment in terms of online reputation.

2.3 Methodology

At the ENTER 25 conference, we will present the initial results of our study comparing actual green practices with customer perceptions, as revealed by AI analysis of customer feedback.

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Green Goals, Digital Tools: How AI and eWOM Can Drive Sustainable Hospitality

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Abstract. Sustainability is a worldwide trend in the hospitality industry. To facilitate sustainable behavior, it is necessary to understand how it relates to customer satisfaction, how sustainability communication affects customer awareness, and eventually how it translates into a return on investment for hospitality decision-makers. Previous research does not consider how eWOM (electronic word-of-mouth) may serve as a data source for influencing sustainable behavior within the hospitality industry.
This study explores how AI can leverage online reviews to understand customer perceptions of sustainability in hotels. By analyzing customer sentiment and awareness, we aim to identify strategies that encourage sustainable behavior and improve ROI for hospitality businesses.

Keywords: eWOM, artificial intelligence, sustainability communication, green practices in the hospitality industry.

1 Introduction and Literature Review

Green practices' definition in the hospitality industry varies. Kim, Lee & Fairhurst [16] defined green practices as "a value-added business strategy that benefits a hospitality operation that engages in environmental protection initiatives". Similarly, Rahman, Reynolds & Svaren [29] defined "green" as "environmentally friendly, that is doing business in a way that reduces waste, conserves energy, and generally promotes environmental health". Myung, McClaren & Li [26] stated that green practices aim to reduce the negative impact on the environment by adopting environmental measures for reducing waste and using sustainable materials and resources [1].
Green practices have been evolving for decades in the hospitality industry, gaining substantial momentum in the 1990s [5] and continuing to grow in importance and significance [27]. Thanks to continuous attention from practitioners [24] the subject of green practices has become a

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research topic of interest in the hospitality literature. Eventually, in order to be economically valuable, green initiatives have to reduce operational cost and create perceived value for costumers [30]. Numerous studies explore the role of hotel green practices in determining guest behavioral intentions [8], showing that hotel commitment towards sustainability is a significant determinant of guest satisfaction [7] [20]. Rogerson & Sims [31] considered that hotels which implement sustainable practices are more competitive because customers expect to find environmental attributes.

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Section 2: Smart Destinations

Sectoral Incentives within the Scope of Smart Tourism Applications

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Abstract. This study examines the pivotal role of government incentives in accelerating the adoption of smart tourism technologies, using Eskişehir, Turkey, as a case study. While the integration of Information and Communication Technologies (ICT) has revolutionized the tourism industry, challenges such as financial limitations and technological complexity impede widespread adoption. Grounded in Innovation Diffusion Theory, this research analyzes how financial, structural, and regulatory support from governments can mitigate these barriers. Based on a cross-sectional survey of 350 tourism businesses, the findings reveal three novel insights: (1) targeted financial grants significantly increase small businesses' willingness to adopt smart technologies, (2) structural support, including knowledge-sharing networks, fosters innovation diffusion among stakeholders, and (3) streamlined regulatory frameworks reduce complexity, enhancing adoption rates. The study provides three actionable policy recommendations: (1) establish tailored financial aid schemes prioritizing SMEs, (2) create regional smart tourism hubs for capacity building and knowledge exchange, and (3) reform regulatory policies to facilitate seamless technology integration. These insights contribute to the development of competitive and sustainable tourism ecosystems.

Keywords: Smart Tourism, Digitalization in Tourism, Government Incentives

1   Introduction

Government intervention in the market has long been a topic of theoretical debate in economic literature, with various schools of thought offering differing perspectives on its role and effectiveness. Laffont provides a broad overview of the arguments surrounding government intervention, noting that while some scholars support the idea of state involvement in correcting market failures, others express strong reservations [1]. Public choice theory, for instance, advocates for the reduction

of government intervention or, at the very least, its limitation within constitutional and legal boundaries [2]. Proponents of this theory argue that government intervention often leads to inefficiencies in resource allocation, distorting the natural functioning of the market and hindering optimal outcomes [3]. In their view, incentive systems designed to encourage certain economic activities or behaviors are inherently 'resource-distorting', disrupting market forces by diverting resources away from more efficient uses.

In contrast, O'Connor presents a critical perspective on the public choice theory, arguing that the state's role, particularly in capitalist economies, is not neutral but rather serves to reinforce the capitalist mode of production [4]. According to O'Connor, the policies advocated by public choice theory often prioritize the interests of capital over those of the wider society, leading to significant welfare losses in certain segments of the population. Gough elaborates on this argument, suggesting that these policies do not necessarily result in welfare gains for society as a whole, but rather deepen social and economic inequalities [5]. O'Connor's critique highlights the importance of considering the distributional impacts of government intervention, particularly in relation to welfare and social equity [4].

A further critical point in the literature concerns the application of incentive systems within specific sectors and practices. While broad critiques of government intervention and incentive policies are important, it is increasingly recognized that the effectiveness of such systems can vary significantly depending on the context in which they are implemented [6]. Sector-specific and region-specific approaches to incentive systems have been found to produce more targeted and meaningful outcomes [7]. In this respect, the application of incentive policies within a particular industry, such as tourism or agriculture, allows for a more nuanced understanding of how these systems operate and what impacts they have on different stakeholders [8, 9, 10].

This sector-specific focus is particularly relevant in the context of this study, which aims to investigate the effectiveness of government incentives within a particular region and industry. Research based on data collected from specific sectors and regions is of critical importance, as it allows for the development of more tailored and context-sensitive policy recommendations [11]. By focusing on a particular industry or geographic area, such research can provide valuable insights into how incentive systems function in practice, highlighting both their strengths

and limitations [12]. Moreover, it can help policymakers to identify potential improvements to the design and implementation of these systems, ensuring that they better meet the needs of the target population [13].

In addition to the theoretical debates surrounding government intervention, there is a substantial body of empirical literature that examines the effectiveness of incentive policies in practice [14, 15, 16]. These studies draw on a range of different perspectives and methodologies, providing valuable evidence on how incentive systems operate in different contexts. Some studies have found that incentive policies can produce significant benefits, particularly in sectors where market failures are prevalent, while others have highlighted the potential for unintended consequences, such as inefficiencies or increased inequality [17]. Overall, the empirical literature underscores the importance of carefully designing and implementing incentive policies, considering the specific characteristics of the sector and region in question.

Smart tourism refers to the integration of Information and Communication Technologies (ICT) into tourism, creating an eTourism ecosystem within an environment of ambient intelligence [18]. This includes various technological tools such as global distribution systems, booking platforms, social media, and mobile apps, enabling interconnected systems and stakeholders [19]. The concept emphasizes co-creation of value through real-time data sharing, Big Data analytics, and personalized services, benefiting all stakeholders in the tourism ecosystem through agile and sustainable management [20]. The implementation of smart tourism technologies can contribute significantly to the overall efficiency and competitiveness of the tourism industry. It allows destinations to provide more tailored and efficient services, while also promoting a more environmentally conscious approach to tourism [21]. In this context, all data related to the promotion of smart tourism policies, particularly within the framework of forecasts included in the development plans, are of critical importance for future policy development and implementation [22].

The primary aim of this study is to assess the role of government incentives in facilitating the adoption of smart tourism technologies within the tourism sector, using Eskişehir, Turkey, as a case study. The study seeks to evaluate how different forms of government support—financial, structural, and regulatory—can mitigate barriers to adoption and foster a more technologically advanced tourism ecosystem.

2 Theoretical Background

Government intervention in markets, including the tourism sector, can be understood through several theoretical lenses. This paper focuses on Innovation Diffusion Theory as foundational to understanding the need for government support in smart tourism. Innovation Diffusion Theory [23] further explains the role of governments in accelerating the adoption of smart technologies. In this theory, adoption rates depend on factors like relative advantage, compatibility, and complexity of innovation. For tourism businesses, smart tourism technologies may seem costly or complex to adopt without clear government-backed incentives or education. Hence, governments play a crucial role in incentivizing early adopters, creating networks for knowledge sharing, and offering financial or structural support to facilitate the widespread diffusion of innovations within the tourism ecosystem.

Innovation Diffusion Theory (IDT), first proposed by Rogers [24], offers a comprehensive framework for understanding how innovations, such as smart tourism technologies, spread through a population over time. According to this theory, the spread of an innovation is shaped by various factors, such as how the innovation is perceived, the communication methods used, the time frame, and the characteristics of the social system where it is introduced [23]. These factors can significantly impact the rate at which new technologies are adopted by tourism businesses.

3 Methodology

This study employs a cross-sectional research design to assess the level of government support required by tourism businesses in Eskişehir to effectively implement smart tourism applications. A quantitative approach was chosen to collect empirical data that can be statistically analyzed to reveal trends, patterns, and relationships within the sector.

3.1 Research Design

The cross-sectional design was selected because it allows for the collection of data from multiple tourism businesses at a single point in time, providing a snapshot of the current attitudes and expectations regarding smart tourism technologies [25]. This design is particularly appropriate

for assessing the effectiveness of government support, as it facilitates the comparison of responses across different types of businesses and identifies potential variations in needs or challenges among them.

3.2 Survey Content and Measurement Scales

The survey instrument was developed based on existing literature on smart tourism technologies and government incentives, with adaptations to align with the study's specific objectives. The survey included three main sections: (1) demographic and organizational characteristics, (2) perceived barriers to adopting smart tourism technologies. Measurement scales were adapted from previous validated studies on innovation diffusion and government support mechanisms, ensuring reliability and content validity.

3.3 Sampling Strategy

The target population consists of approximately 4,000 tourism-related businesses operating within the city of Eskişehir, Turkey. These businesses include accommodation providers, food and beverage establishments, travel agencies, local and intercity transportation companies, entertainment venues, and cultural institutions such as museums. The diversity of this population ensures a broad representation of the tourism sector.

Given the large size and heterogeneity of the population, a stratified random sampling strategy was employed to ensure that key subgroups of the population were proportionally represented in the sample [26]. Stratification was based on business type (e.g., accommodation providers, food and beverage businesses, etc.) to ensure that all relevant sectors were included in the study. Within each stratum, businesses were randomly selected to participate in the survey, minimizing selection bias and ensuring that the sample accurately reflects the composition of the broader tourism sector in Eskişehir.

A total of 350 tourism businesses participated in the study. To determine whether this sample size is sufficient, we conducted a power analysis based on the expected variability in the responses and the size of the target population [27].

For a population of approximately 4,000 businesses, a confidence level of 95%, and a margin of error of 5%, the recommended sample size is

around 350 businesses. This calculation was based on the following formula for sample size determination in a finite population:

$$n = \frac{N \times Z^2 \times p \times (1-p)}{e^2 \times (N-1) + Z^2 \times p \times (1-p)}$$

Where:
N=4000 (population size)
Z=1.96 (Z-score for 95% confidence level)
p=0.5 (estimated proportion of the population with the characteristic of interest, a conservative estimate used when the true proportion is unknown)
e=0.05 (margin of error)

By using this formula, it has been determined that 350 participants would provide statistically reliable results, allowing for meaningful analysis of the key research questions. This sample size is also large enough to account for non-response or incomplete surveys, ensuring the final dataset remains robust [28].

3.4   Data collection

Data were collected via face-to-face surveys conducted between May and June 2024. This method allowed for direct interaction with business representatives, enabling the researchers to clarify any questions or ambiguities in real time. The survey consisted of closed-ended and Likert scale questions designed to capture the businesses' perceived need for smart tourism applications, willingness to invest in smart tourism technologies, and the types of government support they require.

4   Expected Outcomes

Based on the data collected, this study expects to identify several key insights regarding the types of government support that tourism businesses in a tourist destination require to adopt smart tourism technologies. We anticipate that most businesses will express a need for financial assistance, training, and logistical support to transition to smart tourism applications. Moreover, we expect that larger enterprises will be more willing to invest in these technologies compared to smaller

businesses, which may face greater financial and technological barriers. The study also aims to highlight specific policy recommendations that could help a city leverage its tourism potential, particularly in attracting more international tourists through personalized and technologically enhanced travel experiences.

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A Typology of Live Streamers in Tourism

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Abstract. Live streaming plays a crucial role in the real-time co-creation and sharing of travel experiences, as well as in product marketing and destination promotion. There is a growing body of research on the motivations of tourism live streamers and their behavior while streaming. This study, using a live streamer-focused qualitative approach, aimed to: 1) explore the motivations and travel behaviors of tourism live streamers, and 2) develop a typology of live streamers based on their motivations for engaging in tourism live streaming. Findings provide detailed information on the motivations of live streamers and how viewers influence these typologies. Recommendations are offered for tour operators to better target their marketing efforts by partnering with streamers whose content aligns with their products or services.

Keywords: Live Streamer, Typology, Tourism Live Streaming

1   Introduction

Live streaming is revolutionizing the way tourism experiences are presented, enjoyed and marketed [1]. By merging real-time interactive technology with tourism, it has become an invaluable resource for influencers, travel agents and destination marketing organizations [2]. It enables them to bring destinations to life, promote products and engage audiences through immersive storytelling [3]. This dynamic platform offers viewers a direct, engaging and authentic way to virtually explore destinations while interacting with content creators [4]. Streamers can use persuasive communication and emotional engagement to influence viewer behavior, increasing the effectiveness of destination marketing [5]. Research on tourism live streamers can shed light on how streamers shape viewers' perceptions, cultivate trust and influence travel intentions [6, 7]. This study contributes to the knowledge of tourism live

streamers by categorizing them into different types based on their motivations and behaviors.

2   Literature review: from social media to live streaming

The transition from traditional social media to live streaming has marked a shift in the way tourism content is created and shared [8]. Initially, social media platforms allowed travelers to share curated travel experiences through images, videos and text, influencing different stages of their journey, from planning to post-trip reflection [9, 10]. Live streaming offers an immersive, real-time experience, allowing streamers to dynamically engage audiences and showcase destinations as they are experienced in the moment [11]. Unlike traditional social media, which is largely static and asynchronous, live streaming in tourism brings immediacy and authenticity to viewers, who can interact directly with content creators, making the experience more personal and engaging [12, 13]. This live streaming interaction enriches the viewer's sense of presence and connection to the destination by enabling real-time communication [14, 15].

Research is mainly concerned with how viewers are influenced by live streamers, particularly the interaction strategies streamers use to engage their viewers [5, 11]. Viewers' motivations, which include entertainment, relaxation and social interaction, contribute to increased viewer engagement and travel intentions [16]. The interactivity, immediacy and authenticity of live streaming significantly influence viewers' perceptions and engagement with tourism content [14, 17]. Viewers' flow experience, attachment to destinations or even products being promoted could be enhanced by streamers [5]. Their emotional and cognitive involvement could also be deepened by the immersion provided by the streamer's real-time communication, knowledge sharing and entertainment value, leading to higher levels of engagement and participation [11]. This connection increases their intention to travel or make purchases while streaming [12, 14]. Several streaming platforms, particularly in tourism and sports, emphasize value co-creation, where viewers contribute by actively interacting with the content, making requests and providing feedback that shapes the live experience [18]. Most studies have focused on how live streamers influence viewers, rather than exploring the influence of viewers on streamers. Hence, research into the

characteristics and behaviors of tourism live streamers is still underexplored.

3   Methodology

This research adopted a qualitative research approach using semi-structured interviews. Thematic analysis was used to analyze the collected data. Thematic analysis using Nvivo 12 was used to analyze the collected data. Participants were purposively selected from major tourism live streaming platforms in China, including Douyin, Mafengwo.com, Wechat Live Streaming, and Ctrip.com. The inclusion criterion for participants was to have engaged in tourism live streaming at least once in the last two years. A total of 36 in-depth semi-structured interviews were conducted, each lasting approximately 50 minutes. The sample included 20 female and 16 male participants, aged between 20 and 50, with an average live streaming frequency of twice per year. The interview framework consisted of four main sections: (1) motivations for live streaming, (2) the tourism live streaming process, (3) interaction experiences, and (4) differences in travel behavior between those who live stream and those who do not.

4   Preliminary results: tourism live streamer typologies

This study classifies tourism live-streamers into four different types based on their level of commercialization and the frequency of their streaming. They are namely: Income-Oriented Live Streamer, Marketing-Oriented Live Streamer, Experience-Oriented Live Streamer, and Social-Oriented Live Streamer (Figure 1). Each category demonstrates specific behavioral characteristics and patterns.
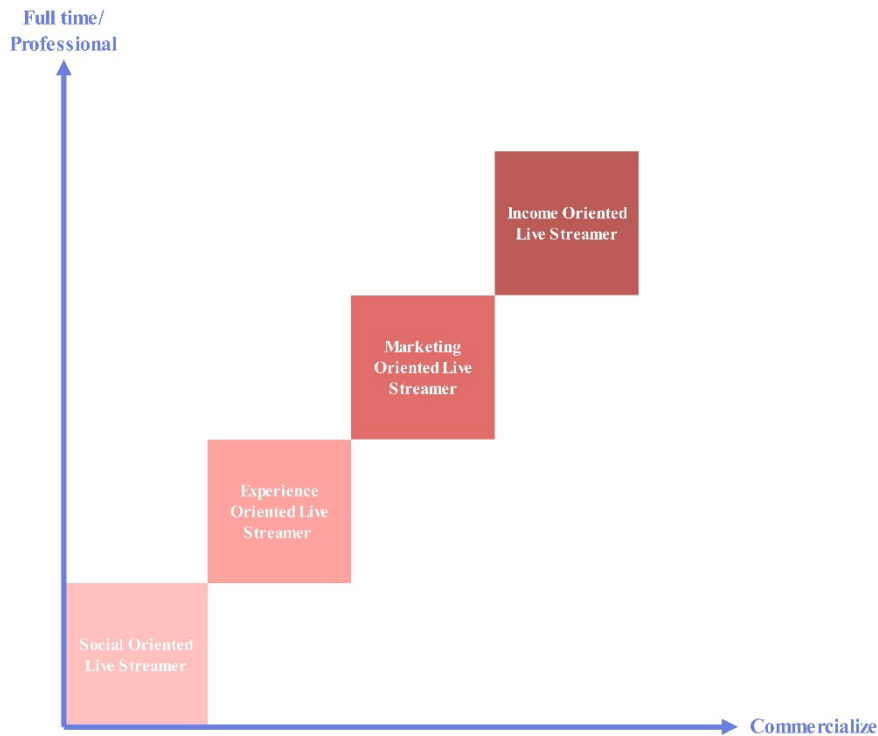
Fig. 7. Axis of tourism live streamer typology

Income-Oriented Live Streamer engages in tourism live streaming as a full-time job. They live stream at least once every day and schedule their live streaming according to the commuting times of their main viewers. If there are special circumstances that require them to be absent from live streaming, they will explain this to their fans in advance. They know their city and the destinations inside out and can show viewers authentic restaurants and local shops. When travelling to attractions or destinations they are unfamiliar with, they research the historical and cultural background beforehand to ensure they can provide valuable information to viewers. When choosing locations, they prioritize places where they can interact with viewers. *"As I climb the mountain, I can show viewers the landscape in all directions along the way. The sights and streets of the ancient city will also be very narrative. But if I just stand by the lake and show the viewers the lake. The viewers might get bored" (Informant 4, male, 35-40).* Their challenge is to balance the viewers' need for scenery with their own need to sell merchandise.

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Profits from the sale of destination-specific food, products, souvenirs and guided tours during tourism live streaming, as well as donations or tips from viewers, are their main sources of income. Some of the Income-Oriented Live Streamers compensate for the costs of the constant travelling by live streaming for an income. They want to escape the 9 to 5 life, or prefer to enjoy a more flexible working conditions, working hours and locations.

Marketing-Oriented Live Streamers use tourism live streaming as an important channel to promote themselves, accumulate fans and build their personal IP. They treat it as a second job, doing it three to four times a week. They come from a variety of professional backgrounds, including students, freelancers and entrepreneurs. Most of their jobs or businesses are related to tourism, culture, overseas study and immigration. *"I am an overseas property investment agent. Some of the viewers may already have investment needs. Through the tourism live streaming, they will get to know and like the city where I live. After the live streaming, they sent me messages to ask about buying property" (Informant 11, female, 35-40).* Tourism live streaming helps them attract more followers and even potential customers. They partner with travel companies to share resources and enjoy freebies to earn non-monetary income. Destination marketing companies, airlines, cruise lines, hotels, attractions and other tourism businesses invite them to share the authentic experiences by offering free services. They specialise in providing viewers with tourism product information, highlighting scenic features or special services offered by tourism businesses in live streaming. Knowing the location, the environment, the route and reading the information provided by the travel company in advance is an integral part of their preparation.

Experience-Oriented Live Streamers are passionate about trying new things and are curious about live streaming. They may occasionally do tourism live streaming. They love to travel and usually have a background of working or studying in the media. The novelty of random communication and unknown interactions with strangers is another motivation. Some of them may be tired of socializing with acquaintances in their daily work and life. Excessive concern and worry from parents and friends may make them feel burdened to share some travel experiences. *"Interacting with viewers who think very differently can take my live streaming into an unknown state. It's possible that their comments*

will change my travel plans. I might visit new places and try new things as a result. All of this is unpredictable" (Informant 9, female, 25-30). Social-Oriented Live Streamers are motivated by the need for a flexible and timely sharing channel. They put their travel plans at the center and focus on expressing their personal emotions and experiences. They rarely plan and prepare live streaming content in advance but they are ready to share their feelings during their travels. They enjoy sharing travel tips with viewers, learning new things and interesting stories about the attractions as they interact. They don't have to struggle to find compatible travel companions and don't have to worry about the loneliness of travel. Tourism live streaming opens a window for them to connect with people from different backgrounds and provides a platform to practice and showcase their expression and knowledge base.

5   Conclusions

This study explored the motivations of live streamers and identified four types of streamers based on their degree of commercialization and streaming frequency. Engaging in tourism live streaming is seen as a dynamic, adaptable, and continuously evolving activity. Tourism live streaming platforms could implement incentive strategies that use gamification methods to encourage and reward streamers. Future studies could investigate how viewer behaviors and communication styles affect live streamers, with a focus on supporting their psychological well-being and encouraging increased participation.

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Smart Agritourism Ecosystems to Improve Local Communities' Quality of Life: Results from a pilot study in Thailand

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Abstract Agritourism has become an important strategy for contributing to rural areas. Higher technological competency can help local farmers participate in agritourism development. Smartness allows tourism stakeholders to co-create real-time experiences and exchange with other stakeholders and tourists via technological platforms. This paper presents the results of a pilot study investigating how smart agritourism ecosystems can improve local communities' quality of life in Thailand. The stakeholder theory is used as the underpinning theory to explore stakeholders' roles and contributions in smart agritourism ecosystems. The Technology Acceptance Model (TAM) and the technology–organisation–environment (TOE) framework are employed to synthesise key success factors influencing agritourism stakeholders to adopt smartness. A pilot study was conducted using semi-structured interviews to collect primary data from farmers and tourism experts in Thailand. The results present emergent factors and their influences on agritourism stakeholders' adoption of smartness in agritourism. The expectation of participants towards a smart agritourism ecosystem was also reported. The research provides a better understanding of the cooperation of agritourism stakeholders through smart agritourism ecosystems to help develop the quality of life of local communities.

Keywords: Agritourism, Quality of Life, Smartness, Stakeholder Theory, Service Ecosystem.

1 Literature and Research Gap

Agricultural tourism (agritourism) is a catalyst for sustainable rural development [1, 2]. Agritourism involves activities conducted on an agricultural farm or similar settings for educational and recreational purposes [3]. The development of agritourism can benefit the local economy, restore farming households, and enhance the quality of life for the

residents [4]. The components of the tourism quality of life can be divided into four categories including: social, physical, environmental, and economic [5]. However, a lack of technology competency, particularly tourism-related technology, often prevents local farmers from participating in agritourism development [6, 7].

Related to the technology utilisation in tourism, smart tourism requires stakeholders to dynamically interconnect via technological platforms and to instantly exchange data and co-create real-time experiences [8]. Smartness enables the efficient development of networks to establish an ecosystem and the dynamic interconnection of all its components [9]. Drawing on systems theory, systems thinking allows academics and practitioners to be aware that resource integration and service exchange are vital for value co-creation [10]. Within service-dominant logic actor-to-actor networks, all stakeholders are resource integrators within a network of involved stakeholders. Hence, all of them have the potential to innovate or co-create value [11].

Agritourism studies should focus more on individual farmers' ability to employ technology and smartness. Also, how agritourism stakeholders could collaborate and share real-time experiences should be investigated. Tourism research must emphasise stakeholder perspectives to understand multiple-actor coordination [12]. Additionally, despite extensive research on quality of life, it is unclear whether the contribution of agritourism providers' technology and smart practices can improve local communities' economic quality of life. A framework is needed to show the collaboration of stakeholders adopting smartness as a catalyst to improve local communities' economic quality of life.

At a micro level, this study focuses on individual farmers regarding the factors that help them integrate technology into their business operations. At a broader level, collaborations among agritourism stakeholders were emphasised to understand their roles. These stakeholders use technology or smartness to enhance their economic status. This co-creation practice helps to propose an ecosystem framework for all the stakeholders. Thus, this paper presents the results of a pilot study on how smart agritourism ecosystems can improve local communities' quality of life in Thailand. The objectives are to identify factors that influence smart technology adoption among farmers and to explore agritourism stakeholders' expectations of a smart agritourism ecosystem to improve their economic quality of life.

Several theories were adopted to underpin the research. Stakeholder theory studies stakeholders' perspectives, roles and the influence of each of them [13]. The Technology Acceptance Model (TAM) aims to identify factors influencing the decision or acceptance of new technologies, offering an individual-level theory of IT acceptance [14]. The technology–organisation–environment (TOE) framework provides an explanation of the factors that affect the acceptance and dissemination of technical innovation at the organisational level, including the technological context, organisational context, and environmental context [15, 16].

2   Methodology

This pilot study employs a qualitative method strategy which allows the researcher to investigate participants' interpretations and connections to construct a conceptual framework and make a theoretical contribution [17]. A purposive, non-probability sampling technique is employed, which allows the researcher to select participants who can best provide data to answer questions [17]. A pilot study data collection was conducted online in April 2023 with two sampling groups in Thailand: ten farmers who use technology in their agritourism business and two tourism experts who are academic university professionals. The average interview duration was 60 minutes.

The questions consisted of five sections: personal and business background, technology adoption, key success factors, smart agritourism ecosystem, and economic quality of life. The TOE and TAM models were key references when preparing the interview questions. Two tourism academic professors have validated the question and data collection procedure. This study gathered data from samples that can represent the actual participants to ensure the reliability of the research. All participants were contacted, appointed, and provided with a consent agreement. The interviews were conducted in Thai, and the recorded conversations were translated and transcribed into English. The saturation relied on the data collected from the participants in the pilot test, which was limited by time and availability. The data were then analysed into themes. The thematic analysis provides a coding system that facilitates qualitative data processing [18]. There is a feature that was encoded as a short sentence or keyword representing a particular concept during translation and transcription. The codes were subsequently analysed

and categorised into major themes. Lastly, the themes were presented as results of the pilot study.

3   Pilot Study Results and Discussion

The results suggested that, the factors that influence smart technology adoption among farmers can be grouped into three themes, technological, organisational, and environmental. Table 1. shows the emergent factors, influences, requirements and involved stakeholders in smart agritourism ecosystems framework.

The proposed framework highlighted that the three themes, technological, organisational, and environmental, were found to have broader aspects that influenced and involved diverse groups of stakeholders. The factors of each aspect pointed to a more individual factor that directly influences each stakeholder. Each factor's influence and requirement were also suggested. These results are consistent with technology acceptance [14-16], rural smartness [15, 19] and smart tourism destination ecosystem literature [20, 21].

Focusing on the improvement of economic quality of life for local communities, which consistent with previous literature [1-5]. It has been expected that the developed ecosystem should provide a well-functioning channel for communication between all stakeholders. The ecosystem should enable stakeholders to collaborate, share information, and enhance their businesses cooperatively. The ecosystem, which connects agritourism providers to their visitors, should support them in terms of sales that lead to an improved economic quality of life. The farmers expected that they could have a higher income and savings. The higher number of existing and potential tourists coming to their farms and these people buying their products generate more revenue for farmers. Job opportunities were expected to be higher. Attracting more tourists to the farm means there are more activities and more job opportunities for local people. Most importantly, the overall community economy should be enhanced. At the community level, there is a general improvement in the economic situation, which influences infrastructure development, financial stability, and effective cooperation.

Table 2. Emergent Themes, Factors, Influences, Requirements and Involved Stakeholders in Smart Agritourism Ecosystems Framework in Thailand.

Themes	Factors	Influences	Requirements	Involved Stakeholders
Technological aspect	ICT infrastructure provision and implementation	Impacting on farmers' ability to operate their business and connect to others	Sufficient provision and maintenance	Farmers, governmental organisations, ICTs providers
	ICT feature and ease of use	Allowing farmers to use and efficiently run their business diversely	Assessment on functions and ease of use	Farmers, academic experts, ICTs providers
	Safety and security	Affecting farmers' decision to use certain ICTs	Assessment of the safety and security of the personal and business information exchange	Farmers, governmental organisations, ICTs providers
Organisational aspect	Capability of organisation and staff	Determining farmers' ability to use ICTs	Training, workshop, and knowledge provisions	Farmers, academic experts, ICTs providers
	Business funding	Affecting technological investment, maintenance, and trainings.	Farmers or owners' financial capability	Farmers
	Ability to connect	Encouraging farmers to collaborate and exchange knowledge with others	Farmers or owners' willingness and social capability	Farmers
Environmental aspect	Financial support	Enhancing farmers' financial capability	External financial supports from related organisation	Farmers, public and private financial institutions
	Technological trends	Affecting farmer' decision to use certain ICTs	Knowledge and update of current trends from related sources	Farmers, governmental organisations, ICTs providers, academic experts
	Competitive pressure	Affecting farmer' decision to use certain ICTs	Exchange knowledge from collaborative groups	Farmers, competitors, networks
	Stakeholder connectiveness	Helping farmers to connect, collaborate, and exchange knowledge	Opportunities to join networks and collaborations	Farmers, local communities, governmental organisations, academic experts, tourism service providers, ICTs providers and others

4   Conclusion

This paper presents the results of a pilot study investigating how smart agritourism ecosystems can improve local communities' quality of life in Thailand. It identifies the emergent factors and their influences on agritourism stakeholders' adoption of smartness in agritourism and highlights the associated requirements and involved stakeholders for those factors. The results from farmers and tourism experts show that several factors influence smartness adoption in agritourism businesses. However, these factors require different support from relevant stakeholders. This paper also reports the participants' expectations of a smart agritourism ecosystem to improve their economic quality of life in terms of higher income and saving, more job opportunities, and overall community economic enhancement. The participant expected that a smart agritourism ecosystem could connect relevant stakeholders, allowing them to collaborate and improve the economic quality of life of the local community. This research provides a better understanding of the cooperation of agritourism stakeholders through smart agritourism ecosystems to help develop the quality of life for local communities. Future research will advance by employing data collection and analysis methodologies with a broader participant group. Hence, the findings will be used to develop a comprehensive framework of smart agritourism ecosystems to enhance the living standards of local communities.

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What content to post on Instagram? Evaluation of engagement in the destination image through tourists and residents

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Abstract. This research examines the engagement patterns on Instagram posts from a destination, leveraging communication and mental imagery theories. The study explores key factors such as sender type (tourists versus residents), content characteristics (pictorial stimuli: places of interest versus hospitality services; centricity: images with people versus without people), and the moderating influence of sender profiles. Employing web scraping, 139,273 posts were collected, with 27,088 analyzed using machine learning and deep learning techniques. A univariate generalized linear model was utilized to evaluate engagement metrics. Findings reveal that images showcasing places of interest generate twice the engagement compared to those featuring hospitality services, while photos without people receive lower engagement overall. Tourist-generated content consistently outperforms resident-generated posts in engagement levels. The moderating role of sender profiles across centricity further influences engagement dynamics. The study provides actionable recommendations for optimizing Instagram strategies in destination marketing.

Keywords: Artificial intelligence, Tourism destination image, Hospitality services, Places of interest, Machine learning, Deep learning, Destination marketing organizations

1. Introduction

Destination marketing organizations (DMOs) use social media to promote their destination image (TDI) [1,2]. Attracting their target audience has become widespread, but it remains a challenge for DMOs to choose the type of content that is liked and attracts the most attention

from users on social media [3]. Photographs have long been an insepa-
rable part of the tourist experience and are also linked to the TDI dis-
played on social media, but they have not been sufficiently exploited in
academic research [4]. The main social media platform where users
share their photographic experiences is Instagram [5], a social media
platform (SMP) full of images, on the one hand from DMOs, but on the
other hand, from tourists and residents themselves. They all share their
photographs with their community, and the latter interacts with the con-
tent through comments and "likes". Since tourists use social media as
an integral part of their travel planning [5], this research attempts to es-
tablish an empirical connection between two academic theories: com-
munication theory [6], and mental imagery theory [7], as the number of
studies on TDI with photographs is limited and there remains a gap be-
tween the theoretical framework and empirical analyses in terms of the
use of visual data in tourism research [4].

The study falls within the scope of communication theory, as it has
been shown that pictorial stimuli can be captured by a user through a
photograph at the destination. Stimuli can be transmitted through a pho-
tograph and are interpreted by the receiver, who interacts with that con-
tent and, however, after carrying out the bibliographic review, it is ob-
served that said theory has not been applied in the context of Instagram
with photographic content. On the other hand, the application of mental
imagery theory is considered appropriate in the present research be-
cause it assumes that individuals mentally represent in their minds the
experience reflected in a photograph.

This study therefore contributes to tourism research and TDI in four as-
pects: firstly, it contributes to academic literature, since the characteris-
tics of the sender (tourist vs. resident) and the type of content shown in
the photographs (point of interest vs. hotel service; with people vs.
without people) have not been taken into account in the analysis of the
pictorial stimuli. Secondly, these variables are investigated using a
large sample composed of 139,273 Instagram posts through the web
scraping technique. Thirdly, artificial intelligence techniques are ap-
plied to extract variables, and finally, the strength of the relationships is
contrasted through hypotheses.

2. Methodology

The data for this research correspond to experiences in places of interest in the city of León, Spain. The choice of a specific destination allows for the identification a priori of both messages and places of interest, which allows for more reliable training of the image recognition algorithm. On the other hand, this choice is consistent with the application of the results in destination marketing, of which this research seeks to be an example of the method to follow [8].

This research has implemented different data download techniques (first phase), structuring and cleaning of the database (second phase), analysis of textual data (third phase) and photographic data (fourth phase), and the final statistical analysis. In total, 139,273 posts shared by Instagram users at the destination were analyzed, using the web scraping technique that allows the automated and rapid download of any data shared on Instagram, such as photographs, texts and metadata, anonymously.

To be considered a tourist from the city of León, two requirements must be met: they must have published photographs of the city of León on Instagram for 30 or fewer consecutive days [9], and they must have published 30 or fewer photographs about said destination on said SMP [10].

After labeling the dataset, sentiment analysis was conducted on the text accompanying the photographs using machine learning methods. Given that tourist experiences are often aimed at eliciting positive emotions and fulfilling desires associated with joy and satisfaction [11], the analysis focused on identifying positive sentiments, excluding neutral or negative experiences, which fell outside the study's scope. A total of 27,088 Instagram posts were analyzed using deep learning techniques to extract insights from the visual content. This was achieved by implementing neural networks within a Python framework, enabling the classification and categorization of various image attributes.

The first neural network identified whether individuals were present in the photographs and determined the number of people depicted in each image. Meanwhile, the second neural network analyzed the type of scene represented, classifying images based on the context they conveyed. This classification, combined with metadata from web-scraped photographs, enabled differentiation between destination-related scenes

(e.g., monuments) and hospitality-oriented settings (e.g., bars, restaurants, and pubs). To evaluate engagement, defined as the sum of likes and comments, the number of followers of the Instagram user sharing the content was also considered [12]. An interaction ratio—calculated as (likes + comments) / followers—was employed to provide a reliable measure of audience perception of the shared images.

3. Results and discussion

The univariate analysis shows that there are significant differences in the engagement obtained when the pictorial stimuli change (points of interest vs. hotel services) (**H1**) ($F_{1,\,27.086}$ = 16.443, p < 0.01). Similarly, significant differences are obtained in the engagement obtained when the type of personal stimulus changes (with people vs. without people) (**H2**) ($F_{1,\,27.086}$ = 3.858, p < 0.01), and there are significant differences in the engagement obtained when the issuer changes (tourist vs. resident) (**H3**) ($F_{1,\,27.086}$ = 5.375, p < 0.01). Furthermore, the mediating role of the sender on the effect of engagement in personal stimuli (**H5**) is significant ($F_{1,\,27.086}$ = 7.036, p < 0.01) and does not differ depending on the type of pictorial stimulus (H4) (p > 0.436).

According to the findings, the type of pictorial stimulus determines engagement (**H1**). Specifically, without distinguishing the type of sender or personal stimulus, photographs related to the point of interest double the engagement rate compared to hotel services (point of interest: 5.23 vs. hotel service: 8.68, average engagement). Another notable result is the differences in engagement between photographs with people and without people, with the latter obtaining a lower engagement rate (with people: 7.79 vs. without people: 6.12) (**H2**). Whether the sender is a tourist or a resident, significant differences in engagement are also observed, with tourists obtaining a higher rate than residents (tourist: 7.94 vs. resident: 5.97) (**H3**). If a tourist shares content, the previous engagement trend continues: if people appear, the user will get more engagement on their photo (with people: 9.90 vs. without people: 5.98). However, if the person sharing the content is a resident, the opposite effect occurs. These types of users get more engagement if their photos do not appear people (with people: 5.69 vs. without people: 6.27) (**H5**). **H4** is rejected. In the case of photos without people, it seems that images of the destination get a higher engagement than those of hotel services

(point of interest: 8.17 vs. hotel service: 4.10), but this difference in means is not significant.

4. Conclusions

This study contributes to a better understanding of destination image formation (DI) on SMPs, specifically on Instagram [132]. The results allow us to know which photographic stimuli receive the most attention from user communities through engagement. The findings of this study also expand the literature on user behavior on the SMP Instagram, by aligning two theoretical constructs that explain, on the one hand, how users perceive the destination's photographic stimuli and, on the other, how they interact with it. The theory that frames this research is the communication theory, in which an issuer (Instagram user, tourist vs. resident) intentionally sends a message (post about point of interest vs. hotel service) to a receiver who interacts with the content (reception and interaction through engagement). This reception involves the theory of mental images, which explains how users can imagine living the experience observed in a photograph, and therefore interact with the content through likes and comments. It is surprising to find that both destination and hotel service photos get more engagement when people appear in the images. Both landmark and hotel service photos get more engagement when the sender is a tourist. This may be because when tourists photograph the destination, they show their community new experiences outside of their daily lives, while when residents show their daily life, which their community is probably more familiar with, they are less surprised by them and therefore get less engagement. This research expands the literature on destination marketing management by empirically testing the effect of different stimuli that, through the mental images created by the receivers, affect their behavior on SMP.
This research allows us to propose strategic lines of action for both destination managers and hospitality service managers, as well as for Instagram users themselves. Therefore, recommendations can be made to different types of content creators to improve their engagement. Tourists, when posting a tourist experience on their Instagram profile, should focus on showing the people who live and enjoy the trip, as the results of this research show. However, residents who want to see their engagement rate increase should be concerned with spreading images

that are not focused on people, but rather on the services they are enjoying, showing their community the novelty of their experience. Specifically, the business implications are related to hospitality services. To improve their engagement, they should focus on posting photographs with people enjoying the service, in any case. In addition, according to the findings, the type of pictorial stimulus determines engagement. Specifically, regardless of the type of sender or personal stimulus, photographs related to the place of interest double the engagement rate compared to hospitality services, a direct implication for TDI managers who want to improve their image and attract potential tourists to their destination. You should incorporate people enjoying the experience in your images about the destination.

This study acknowledges several limitations that could be addressed in future research. Firstly, it focuses on a single destination—a cultural and gastronomic inland location—which may limit the scope of its findings. Validation in diverse destinations, such as beach resorts, mass tourism hubs, or shopping destinations, is recommended. Secondly, the dataset of 150,000 Instagram posts primarily reflects positive tourist experiences, potentially restricting the generalizability of the results. Future studies could explore these insights across a broader spectrum of experiences, including negative ones [14]. Thirdly, factors such as image quality, viewer personality, or the social media platform environment may hinder mental image formation. Since these variables cannot be controlled in a non-experimental setting, further research could investigate their influence on user behavior using advanced methodologies like neuromarketing or geolocated social media analysis [15]. Additionally, other sensory-rich formats on Instagram, such as videos with sound, offer promising avenues for understanding how visual content shapes mental imagery.

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Section 3: AI & Robots

AI-Driven Collaboration and Creativity: Enhancing Ideation in Hospitality and Tourism

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Abstract. This paper examines the transformative role of artificial intelligence (AI) in the ideation processes of AI-Enhanced Creatives (AIEC) within the hospitality sector. As businesses increasingly rely on data-driven insights and prioritize personalized customer experiences, it is essential to understand how AI tools facilitate collaboration and creativity among non-traditionally trained creatives. The study underscores the integration of AI technologies, including generative AI applications, which provide cognitive stimuli and structured frameworks that enhance the ideation process. Through a quantitative survey-based methodology, this study investigates the impact of AI tools on the ideation dynamics between AIEC and traditional creative teams while also addressing the ethical considerations and challenges associated with AI integration. The findings indicate significant implications for creativity, employment, and the future trajectory of innovation in the hospitality industry. This research contributes to the expanding body of literature on AI's influence on creative processes. It offers practical insights for industry stakeholders seeking to leverage AI for enhanced collaboration and innovation.

1   Introduction

The modern world is abundant with data, and many businesses are increasingly reliant on the information derived from data generated during their operations (Doborjeh et al., 2022). Moreover, customer desire to participate in the design of the products and services leads to a new paradigm (Hu et al., 2011), enhancing customer engagement in a more personalized way (Aksoy et al., 2021). The integration of artificial intelligence (AI) into creative processes is reshaping how professionals generate ideas, collaborate, and innovate across industries. This shift is particularly profound in the hospitality sector as the need for fresh and

creative solutions to meet evolving customer demands grows. AI refers to systems that aim to replicate human cognitive processes, including learning, reasoning, and problem-solving (Doborjeh et al., 2022). Over time, AI has garnered substantial attention in both literature and practice (Bulchand-Gidumal et al., 2023; Dwivedi, Kshetri, et al., 2023; Knani et al., 2022; Law et al., 2024). One of AI's most significant contributions lies in its ability to enhance marketing efficiency through sophisticated data analysis, personalized content generation, and process automation, fundamentally transforming marketing strategies. AI-powered tools such as ChatGPT, Jasper, and DALL·E have facilitated the rise of AI-Enhanced Creatives (AIEC), professionals who leverage artificial intelligence tools to develop and refine creative content, such as marketing materials, guest experiences, and service innovations to produce high-quality work and enhance personalization (Bulchand-Gidumal, 2020; Bulchand-Gidumal et al., 2023; Knani et al., 2022). Additionally, AI has been incorporated into a diverse range of applications within the tourism and hospitality industries, including personalized recommendations, robotics, chatbots, virtual travel agents, predictive analytics, language recognition, and more (Bulchand-Gidumal, 2020). Such applications underscore AI's pervasive influence and its potential to reshape the service sectors.

Placing customers at the center of the inquiry, it is essential for businesses to establish a strategic vision for generating new ideas as the foundational pillar of the innovation process. However, the specific impact of AI on the ideation process for AIEC remains underexplored, especially regarding how AI facilitates collaboration between professionals with diverse skill sets. The ideation phase, crucial to marketing professionals, is where initial concepts are formulated and creative directions are established. Traditionally, this process has relied on human creativity and team brainstorming. The dynamics of ideation are undergoing transformation with the introduction of AI-driven tools that provide cognitive stimuli and structured frameworks.

Scholars have called for more empirical research on AI, especially to identify and predict entrepreneurial characteristics and performance outcomes of individuals, teams and organizations (Filieri et al., 2021). The contributions of this study are threefold. First, this study explores and delineates the influence of AI tools on the ideation process among non-traditionally trained creatives in people-oriented industries such as tourism and hospitality. It examines how AI tools facilitate the ideation

process for AIEC, enhance collaboration between AIEC and creative teams, and address the challenges and ethical considerations associated with integrating AI into workflows. The research further considers the long-term implications of AI integration for creativity and employment within the hospitality sectors.

2   Literature Review

The development of the Internet, social media, websites, smartphones, smart applications, and the overall virtual world changed how information is distributed and how people plan and consume (Buhalis et al., 2022; Dwivedi, Pandey, et al., 2023) products and services. Personalization, known as one-to-one marketing (Arora et al., 2008), is a specialized form of product and service differentiation and is an essential element of customer experience (Ozturk et al., 2017). Creating personalized and memorable customer experiences has always been at the heart of the service industry (Oyner & Korelina, 2016).

The selection of the best ideas can be costly due to the limited number, objectivity attention, and experts' skills (Bell et al., 2024). Integrating AI tools into ideation processes has garnered increasing attention for its potential to enhance creativity, particularly among *non-creative* professionals engaged in creative, customer-facing projects (Creely & Blannin, 2023).

AI tools such as GPT, DALL·E, and MidJourney have been shown to support idea generation by providing cognitive stimuli that lead to novel solutions. AI promotes cognitive priming effects, encouraging ideation that surpasses conventional solutions, which is particularly beneficial in settings where traditional brainstorming may be limited (Grech et al., 2023). This aligns with the emphasis that AI facilitates a mixed methods approach to ideation, allowing for qualitative and quantitative evaluations of creative processes (Koch et al., 2019). Additionally, generative AI in design contexts automates repetitive tasks, freeing time for more creative activities (Bagnato, 2023). This automation is especially valuable for *non-creative* professionals who may lack the time or expertise to immerse themselves in creative processes.

Within hospitality, AI applications have played a key role in speeding up the time-to-market for various initiatives (Samara et al., 2020). Intelligent automation can enhance the pre-trip experience for travellers,

streamlining tasks such as information gathering and reservations (Filieri et al., 2021). This automation improves customer experience and enables businesses to scale their marketing efforts more efficiently, including personalized recommendations. AI technologies can also improve service delivery and operational efficiency (Doborjeh et al., 2022). These advancements allow *non-creative* professionals to leverage AI for improved decision-making and innovation in service offerings, further reducing creation and delivery lead times.

3   Methodology

This study aims to explore if and how AI can contribute to the ideation process to inform the direction for further inquiry and understanding (Eriksson et al., 2020). It employs a quantitative survey-based approach to examine how AI tools influence the ideation processes of AIEC in hospitality. The research employs a positivist paradigm that systematically collects data from professionals working within the hospitality sector, particularly those that support ideation, collaboration, and strategy development. The deductive approach will explore pre-defined research questions. This approach builds on an AI and hospitality studies framework that emphasizes the role of quantitive data in assessing technological integration's impact on creative processes and collaboration (Law et al., 2024).

Participants will be recruited using purposive sampling, with the survey administrated via online crowdsourcing platforms (e.g., Mechanical Turk) to access a broad range of professionals in the hospitality industry. The survey will also be shared via social media platforms such as LinkedIn, Facebook, and Instagram. The sample population will include domestic and international professionals from the hospitality industry. The focus is on individuals with varying levels of experience in marketing and creative collaboration. The participant pool will include those working directly in ideation roles and those in supporting capacities for AIECs. The data will be gathered using a structured self-administered questionnaire measuring participants' awareness and implementation of AI tools for AIEC. The questionnaire will include standardized items assessing various variables such as the use and effectiveness of AI tools, collaborative dynamics, or perception of creativity. Data

analysis will include descriptive statistics, and analysis such as Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), correlation analysis, covariance analysis (ANCOVA), and t-tests.

4   Conclusions and Future Research Directions

The added value of this research lies in its exploration of how AI can enhance ideation processes, particularly for AIECs in the hospitality sector. By examining AI's potential to facilitate collaboration between non-creative professionals and traditional creative teams, this study highlights the capacity of AI to drive innovation through cognitive stimuli and structured frameworks.

This research makes theoretical contributions by advancing the understanding of AI's influence on creativity and collaboration in non-traditional settings, particularly hospitality. It introduces AI as a crucial tool for enhancing ideation. It broadens creativity theories by framing AI as a collaborator in the creative process, especially for professionals lacking formal creative training.

Practically, the study provides valuable insights for industry stakeholders on leveraging AI to improve innovation and efficiency. It offers a framework for how AI can enhance ideation, accelerate time-to-market, and foster interdisciplinary collaboration while addressing ethical concerns such as bias and intellectual property protection.

Future research can investigate the long-term impact of AI on creative processes, whether AI tools continue to drive innovation or foster dependency, affecting human creativity over time. Additionally, exploring AI's role in interdisciplinary collaboration is crucial, as AI tools may bridge gaps between professionals in diverse fields within tourism and hospitality, such as marketing, operations, and service design. Further research should also focus on the ethical implications of AI in ideation, examining biases in AI-generated content, intellectual property issues, and the effects of AI on employment in creative industries. Lastly, exploring the customization of AI tools to meet the specific needs of luxury travel or eco-tourism will ensure AI's relevance and effectiveness in diverse industry contexts.

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The Role of AI Transparency in Traveler Trust: From Secretary to Advisor

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Abstract. Role of AI transparency in Traveler Trust, focusing on its potential to transition from a secretary to an advisor. Utilizing a 2x2 experimental design, we explore how AI transparency (high vs. low) and task version (item vs. unspecified) affect trust. The research aims to determine if AI transparency can enhance trust, especially in unspecified tasks, by providing clarity and reducing uncertainty. By understanding these dynamics, we can optimize AI systems to better meet diverse traveler needs, potentially transforming AI from a basic assistant into a strategic advisor in complex decision-making contexts.

Keywords: AI Transparency, trust, Task version, Role of AI

1   Introduction

The rapid advancement of artificial intelligence (AI) technology has significantly increased its use in the tourism domain [7, 15]. As AI becomes more integrated into various aspects of trip planning, understanding how it influences travelers' trust has become increasingly important [14, 12]. Specifically, AI transparency, including explainability and causality, plays a critical role in shaping perceptions of trust .

This study explores how AI transparency, as an independent variable, affects travelers' trust, with task version as a moderating factor. The study categorizes AI roles based on task versions as either assistant or advisor.

AI systems are now used not only as assistants performing routine tasks but also as advisors providing strategic insights . The distinction between these roles heavily relies on trust, which is significantly influenced by the transparency of AI processes . Transparency helps users feel more in control and leads to a more satisfying experience by reducing uncertainty and providing clarity in interactions [16, 9].

For example, when users receive transparent explanations for AI recommendations or actions in customer service settings, their trust in the system can be enhanced . In contrast, non-transparency—where users are not informed about the system's processes—can lead to frustration and lower satisfaction, particularly when AI makes unexpected decisions or recommendations .

This lack of transparency can leave users feeling disconnected from the system, ultimately reducing their overall trust in the interaction [1, 14]. The effectiveness of AI in its roles as either assistant or advisor also depends on the user's ability to trust its outputs, especially in high-stakes or complex decision-making contexts . For instance, in customer service and wealth management contexts, systems that provide transparent feedback and explanations foster higher trust, as users appreciate understanding how and why the AI arrived at specific recommendations [13, 5].

Thus, AI systems are increasingly being used not only as assistants performing routine tasks but also as advisors providing strategic insights. The distinction between these roles depends significantly on user trust, which is influenced by the transparency of AI processes. Therefore, this study investigates how transparency affects trust in AI systems and how task versions moderate this relationship.

2 Literature Review

2.1 Task version modified by prior determinability

Byström and Järvelin (1995) defined the concept of prior determinability as the ability of searchers to clearly understand and define the required information, as well as to select appropriate methods or procedures to achieve their goals . Capra et al. (2017) expanded on this concept by developing two types of task versions: Item and Unspecified task. For example, they examined different levels of determinability by framing tasks related to cold treatment as either comparative tasks with specified items (e.g., "name of herb") or open-ended questions with unspecified dimensions (e.g., "method") . O'Brien et al. (2020) further explored task complexity by measuring prior determinability using the task versions proposed by Capra et al. (2017) .Therefore, this study adopts the task versions proposed by Capra et al. (2017) to distinguish between the roles of AI as assistant and advisor.

2.2 Enhancing Trust Through Prospective Transparency

Transparency in AI systems, especially in decision-making, has been found to positively influence users' trust and perceptions . Transparency enhances user understanding of how AI arrives at decisions and fosters trust by addressing concerns about the "black-box" nature of AI systems . Xu et al. found that when AI systems are transparent about their inner workings, users tend to perceive these systems as more trustworthy and socially intelligent .
According to Felzmann et al. (2019), transparency can be divided into prospective transparency and retrospective transparency. Among these, prospective transparency is defined as focusing on "informing users in advance about the data utilized and the general mechanisms by which the system operates." This proactive approach aims to clarify how decisions are typically reached, serving as a form of accountability mechanism (Zerilli et al. 2019) [4, 18]. Accordingly, this study adopts the concept of prospective transparency, positing that providing users with prior information about the operation of data mechanisms can enhance both the accuracy of information and trust.

2.3 Travelers trust in AI

Research indicates that transparency enhances trust by providing clear explanations of AI processes, particularly in contexts that require high cognitive engagement, such as travel planning and complex decision-making [6, 9]. Additionally, when AI systems effectively address problems through demonstrated competence and perceived intelligence, they foster user confidence by showcasing reliability and problem-solving capabilities . These findings support the hypothesis that AI systems with high transparency and the ability to solve complex problems can significantly enhance traveler trust.

3 Research Model and Hypotheses Development

This research investigates how AI transparency impacts traveler trust and how task version moderates this relationship. By suggesting scenarios with varying task demands—ranging from comparative items to unspecified dimensions and problem-solving tasks—this study aims to explore the influence of AI transparency on trust by categorizing tasks

into different versions. Thus, the research model is outlined as follows in Figure 1.

Hypothesis 1: *AI transparency will have a significant effect on trust*

Hypothesis 2: *Task version will moderate the relationship between transparency and trust, such that task version will lead to higher trust than item task version, especially in high transparency.*
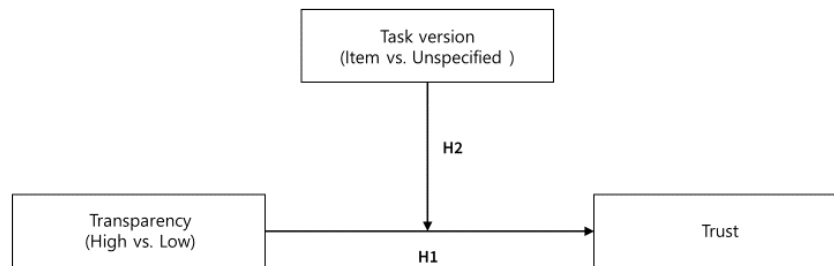
Fig. 8. Research Model

4　　Research Methodology

In this study, the role of AI is categorized based on task complexity: **Item tasks** represent low task complexity and are aligned with the role of an AI assistant, while **Unspecified tasks** represent high task complexity and reflect the role of an AI advisor. Accordingly, the experiment employed a 2×2 between-subjects design, with factors being AI transparency (high vs. low) and task version (Unspecified vs. Item). At the beginning of the study, participants were presented with an introduction and a scenario involving the use of AI for travel planning (e.g., planning a trip to Bali). They will then show stimuli and be asked to respond to three items related to trust (e.g., "I feel that the information about travel provided by the AI system is honest and authentic.") using a 5-point Likert scale (1 = Strongly disagree, 5 = Strongly agree).

Table 3. Example of task versions.

Item task	What are the differences between the prices of Hilton Hotel and Sheraton Hotel in Bali?
Unspecified task	What are the key factors to consider when comparing hotel prices in Bali, and how do these factors differ?

Table 2. Stimuli for studies

	Item task	Unspecified task
High transparency		
Low transparency		

5   Conclusion

This study raises important questions about the future role of AI as both assistants and advisors. By examining the interaction between AI transparency and task versions, we gain valuable insights into how AI systems can be optimized to meet the diverse needs of travelers. If AI can effectively adapt to varying levels of task complexity while maintaining transparency, it has the potential to evolve beyond simple assistance to become a trusted advisor in complex decision-making processes.

As AI technology continues to advance, its role could expand significantly, shaping how individuals and organizations approach problem-solving and strategic planning. Ultimately, this research highlights the importance of leveraging AI to enhance decision-making capabilities,

fostering a future where AI serves as both a reliable assistant and a strategic advisor.

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Robotic Hospitableness: The Role of Nonverbal Communication in Enhancing Guest-Robot Interactions

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Abstract. As AI technologies continue to evolve, successful reciprocal guest-robot interactions are increasingly becoming a key goal for hospitality providers. However, nonverbal communication – a crucial component of interaction – has yet to be thoroughly examined in this context. This project focuses on how nonverbal cues can convey 'hospitableness' within guest-robot interactions. Given the exploratory nature of the study, this paper proposes the use of semi-structured interviews that combine unprompted and prompted responses supported by AI-generated video-elicitation. Guided by the existing literature on human hospitableness and relevant nonverbal communication works, an abductive approach – combining both inductive (bottom-up) and deductive (top-down) reasoning – will be employed to analyze the qualitative data. The anticipated findings will provide both theoretical and practical insights into fostering hospitable human-robot interactions by proposing a framework for robotic nonverbal hospitableness, including key elements such as physical appearance, proxemics, kinesics, paralanguage, and haptic interactions.

Keywords: Nonverbal communication, Human-robot interaction, Hospitableness, Video-elicitation interview, Abductive approach

1   Introduction

The integration of robots into roles traditionally occupied by humans is reshaping our understanding of interpersonal communication. In the tourism and hospitality industry, this shift introduces new challenges for understanding human-robot interaction (HRI), given the relational and experiential nature of host-guest engagements. As tourism services are fundamentally experiential, these interactions extend beyond transactions, involving emotional engagement, trust-building, and cultural sensitivity [1, 2]. Nonverbal cues, such as smiles and gestures, are crucial for fostering emotional connections, facilitating value exchange,

and co-creating meaningful experiences [3, 4]. Yet, the significance of these non-verbal communications in HRI has been largely overlooked. Previous HRI research has tended to focus on technical design aspects [5 ,6, 7], neglecting the emotional and experiential needs central to hospitality. This study aims to conceptualize how nonverbal cues in HRI can embody the core value of *hospitableness*. Drawing on interdisciplinary literature and employing a mix of unprompted and AI-supported video-elicitation interviews, this research explores how robots can replicate or enhance hospitable interactions through nonverbal communication.

2 Literature Review

2.1 Nonverbal Communication in Human-Robot Interaction

The critical role of nonverbal communication in human interactions has spurred researchers in human-robot interaction (HRI) to investigate how robotic movements and expressions can effectively convey emotions. Roboticists argue that research into expression in robots should adopt a case-by-case approach, as not all components and sensors function in the same way [7]. Features such as head movement [5], gaze patterns [6], and LED components [7] have been identified as important elements for conveying robotic emotions. However, much of this research focuses on optimizing mechanical functions, sensor efficiency, and movement precision, often neglecting the experiential context that is vital to fields like tourism and hospitality.

2.2 Nonverbal Communication in Hospitality Host-Guest Communication

Managing host-guest interpersonal relations through meaningful interactions is recognized as a critical component of successful tourism and hospitality services. Some researchers argue that nonverbal cues may have an even greater impact than verbal communication [8]. Studies suggest that more than half of the communication that takes place between humans consists of nonverbal exchanges [9]. Nonverbal communication encompasses four major areas: physical appearance (e.g., grooming), proxemics (e.g., social distance), kinesics (e.g., gestures),

and paralanguage (e.g., tone) [12]. In the context of tourism and hospitality, nonverbal communication acts as a bridge for value exchange between hosts and guests, facilitating mutual recognition (e.g., breaking the ice and alleviating initial unfamiliarity) and relationship building (e.g., signaling understanding and respect) [3]. Central to this field is the host-guest relationship, where cues such as warm smiles, welcoming gestures, and sustained eye contact are vital in conveying 'warmth,' 'empathy,' and 'personalization,' fostering a sense of comfort, trust, and attentiveness [11].

2.3 Embodying 'Hospitableness' via Robotic Nonverbal Cues

Unlike other self-service technologies, the 'embodiment' of robots enables them to exhibit unique nonverbal cues that can convey hospitableness through 'welcoming' and 'caring' gestures. In response to ongoing criticisms in the 'tech-touch' debate that technology-driven services lack human touch and emotional connection, robots designed to mimic human behaviors offer a promising medium for expressing hospitableness through nonverbal cues [12].

Despite ample research on robot anthropomorphism in tourism and hospitality, this paper contends that simply designing robots to appear more 'human-like' is insufficient for achieving the level of hospitableness expected in the tourism and hospitality fields. As the HRI literature suggests, "… Depending on the specific robot, not all of these cues might be available or utilizable as they are in humans" (pp. 570) [7]. This underscores the limitations of merely replicating human behaviors. Further research is required to explore how robots can embody core hospitality values through nonverbal cues that differ from traditional human communication. Effective design should enable robots to convey 'warmth,' 'empathy,' and 'personalization,' ensuring their integration into hospitality environments meets guests' emotional and experiential needs.

3 Methodology

3.1 Combining Unprompted and AI-Supported Video-Elicitation Interviews

Given the exploratory nature of this study, a qualitative approach using semi-structured online interviews was adopted. The interviews began with participants sharing their experiences of hospitableness in human interactions, setting the stage for a deeper exploration of robotic hospitableness. The focus was placed on three key robotic service touchpoints: greetings, check-in procedures, and farewells. Each touchpoint consisted of both unprompted responses and prompted responses elicited using an AI-generated video.
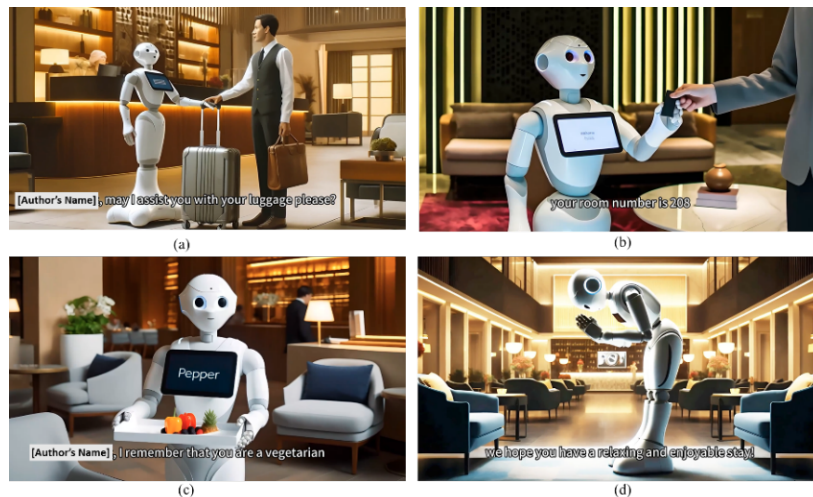
Fig. 9. Self-Produced AI-Supported Video Screenshots

A two-minute video was designed to present three service touchpoints during check-in, including greetings, check-in procedures, and farewells. The video showcased various types of non-verbal communication at each touchpoint. For example, during the **greetings**, the robot used a welcoming gesture, such as a static wave, and made prolonged eye contact to acknowledge the customer's presence. During the **check-in procedures**, the robot alternated its gaze between the customer and other devices to signal multitasking while smiling subtly to maintain natural interaction. Finally, during the **farewells**, the robot waved to the customer and bowed slightly to convey respect and ensure a positive

closing to the interaction. The whole video will be presented during the conference presentation (See Figure 1 for screenshots).

3.2 Data Collection and Analysis

Following testing and pilot interviews with five participants, online interviews were conducted with 20 participants from 12 different countries, spanning a broad age range of 18 to 60, various occupations and educational backgrounds. Utilizing an abductive approach, the data were analyzed through thematic analysis. This process was guided deductively by drawing on existing concepts of *hospitableness* and literature on nonverbal communication while also allowing new themes to emerge inductively from the data.

4 Preliminary Results

As the project is ongoing, the following results are preliminary and may evolve as additional data are analyzed and new insights emerge. The preliminary research findings suggest that nonverbal cues significantly enrich hospitable interactions, extending beyond basic communication to foster perceptions of authenticity and individual attention. Effective human-robot relationship building is contingent upon the robot's ability to exhibit behaviors that are not only appropriate and engaging but also deeply resonate with human expectations of genuineness and personalized care.

Critical elements include **physical appearance**, exemplified by robots displaying smiles; **proxemics**, defined by the social distances maintained between humans and robots; **kinesics**, including culturally resonant gestures such as bows or waves; **paralanguage**, characterized by softer, gentler tones; and **haptic interactions**, such as thermally-enhanced handshakes. Respondents even expressed a willingness to forge 'friendships' with robots that are highly personified and able to adeptly navigate the 'uncanny valley' effect. This suggests a significant opportunity to further explore and understand how robots can embody hospitableness using non-verbal cues, ultimately enhancing guest experiences in tourism and hospitality settings.

5   Implication

Theoretically, this project is expected to break new theoretical ground by extending traditional concepts of hospitableness into a robotic context by understanding how nonverbal cues can be optimized to transmit human warmth and genuineness. Practically, these insights offer a foundational blueprint for AI designers in tourism to develop and refine robotic behaviors that not only ensure efficiency but also enhance emotional engagement, positioning robotic interactions as a core component of the customer service strategy within the tourism and hospitality industry.

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Anthropomorphism-Based AI Robots in Tourism and Hospitality: Themes, Theories, and Future Research Agenda

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Abstract. This study presents a framework for future research on anthropomorphism-based AI robots in the tourism and hospitality industries. Relevant articles were systematically filtered for analysis using the PRISMA selection method. Five key themes related to anthropomorphism-based AI robots are proposed, namely 1) anthropomorphic attributes; 2) service contexts; 3) adoption intention; 4) interaction experience; and 5) post-interaction and ethical recommendation. Based on the themes presented, potential questions for future research are proposed, accompanied by a review of the underlying theoretical perspectives.

Keywords: Anthropomorphism, AI robots, Service Robots

1 Introduction

Human-Robot Interaction (HRI) is a multidisciplinary field that explores the interactions between humans and robots, encompassing various aspects of design, communication, and practical application [3]. HRI aims to develop systems that enable robots to engage with humans in meaningful and effective ways, fostering collaboration and enhancing the user experience across various contexts, including tourism and hospitality. A critical element in HRI research is the concept of embodiment, particularly in relation to a robot's morphology or physical appearance [10]. Robot morphology can be classified into several categories, including anthropomorphic (*human-like*), zoomorphic (*animal-like*), caricatured (*cartoon-like*), and functional (*machine-like*) designs [14, 15, 12]. In the tourism and hospitality industry, the increasing use of anthropomorphic robots is significantly impacting customer interactions and experiences [10]. [10] emphasize that a customer's initial interaction with a service robot often creates a "wow factor," making the robot appear "pleasant to look at" and "cool." However, the uncanny valley theory suggests that if the robot's appearance is not matched by adequate functionality and performance, it can lead to negative customer reactions [12].

Although research on Human-Robot Interaction (HRI) has expanded significantly in recent years, driven in part by the Covid-19 pandemic, expert opinions and findings remain divided regarding the impact of robot anthropomorphism on customer experiences [11, 13]. This study explores the theoretical foundations and future research directions of anthropomorphic AI robots in tourism and hospitality. The study addresses the primary themes related to anthropomorphism-based AI robots and the potential future research agendas.

2   Methodology

A systematic literature review was conducted using two major databases, Scopus and Web of Science. The PRISMA selection method proposed by [8] was employed, with the following keywords: (Robot or Humanoid or Chatbot) and (Anthropomorphism) and (Hospitality or Restaurant or Hotel or Food). This study only included empirical articles, written in English, and publications from tourism and hospitality journals ranked 1 to 4 according to *The Chartered Association of Business Schools Academic Journal Guide 2021*. Following a thorough assessment based on inclusion and exclusion criteria, 32 articles were selected from A and A* ranked journals in CABS, all of which are pertinent to this study.

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                  Initial search
        (ROBOT* OR HUMANOID* OR CHATBOT*) AND
   (ANTHROPOMORPHISM) AND (HOSPITALITY OR RESTAURANT*
              OR HOTEL* OR FOOD*)


Records identified (n = 509)          Records removed before the
   ScienceDirect = 399                screening:
   Web of Science = 89                Duplicate records = 151
   Additional Record = 21             Irrelevant articles = 259
                                      Conference proceeding = 8


                                      Article excluded (47 articles):
                                      - Other than subject areas:
                                        business, management, and
   Articles screened:                   accounting; computer science;
   (n = 91)                             social science; psychology
                                      - Other than empirical and
                                        review articles.
                                      - Other than English.


   Full-text articles assessed        Article excluded:
      for eligibility                 Irrelevant content (n = 12)
        (n = 44)


   Articles included in the
          review
        (n = 32)
```

Identification / Screening / Inclusion

This study analyzes the variables identified in 32 collected articles and organizes them into different research themes. These themes serve as the foundation for constructing a future research recommendation.

3 Key Research Themes

The selected articles identify five relevant research themes on anthropomorphism-based AI robots, namely: 1) anthropomorphic attrib-

utes; 2) service contexts; 3) adoption Intention; 4) interaction experience; and 5) post-interaction, with distinct patterns, as illustrated in Figure 1.
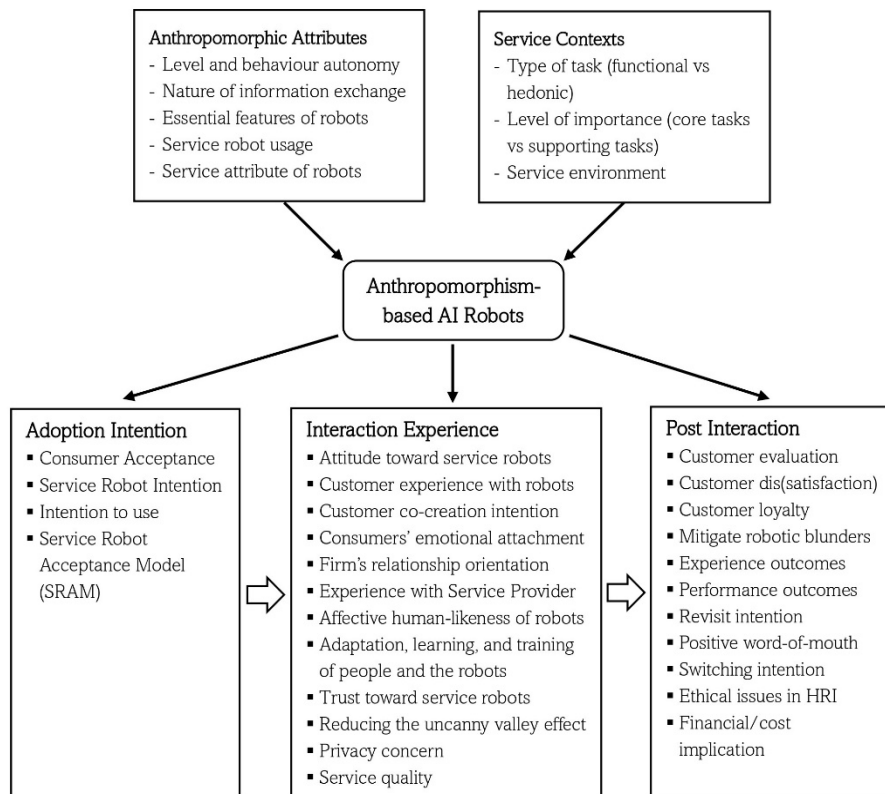
Figure 1. Key research themes on anthropomorphism

Anthropomorphic attributes play a key role in shaping guests' interest in interacting with AI robots. Beyond having a human-like appearance, service robots in the tourism and hospitality industries must have features and capabilities aligned with their physical form. [12] note that interactions will fall short if the robot's performance does not meet expectations. Therefore, a robot's autonomy and behavior are crucial factors in service delivery [3]. Robots that can collaborate with both humans and other robots display a high level of autonomy. Additionally, robots must facilitate mutually beneficial interactions through information exchange, requiring three of the five human senses: vision, hearing, and touch [3]. Studies have also emphasized the importance of gestures, language, interfaces, and physical interactions [4, 14]. In

terms of **Service contexts**, the physical environment in which the robots operate must be tailored to the type of tasks they perform. These tasks can be either functional or hedonic in nature. Mechanoid robots typically handle functional tasks, while humanoid and android robots are better suited to fulfilling hedonic needs [12]. It is important to consider whether the robot serves as a primary service provider or merely supports human servants. These factors are critical considerations for service providers [12].

Adoption intention reflects the level of interest and likelihood that an individual is willing or likely to use AI robots in tourism and hospitality services, influenced by factors such as anthropomorphic or human-like features. Various studies represent this intention using different variables, such as customer acceptance, service robot intention, and intention to use [5, 6, 9]. These factors help predict whether individuals or businesses will ultimately adopt a new system, such as AI robots. **Interaction experience** refers to how guests or customers interact and engage with robots [7, 13]. It includes factors such as ease of use, comfort, communication quality, and the robot's responsiveness to users' needs and expectations. This experience is shaped by various factors, including the robot's anthropomorphic behavior, its ability to understand and respond to users, and the smoothness and satisfaction of the interaction [2, 14]. Interaction experience plays a critical role in influencing users' attitudes, their intention to co-create value, emotional attachment, perceptions of service quality, trust, and concerns about privacy when using AI robots. **Post-Interaction Experience** refers to the evaluation, feelings, and impressions that users have after interacting with AI robots in tourism and hospitality settings [7]. This evaluation includes customer satisfaction or dissatisfaction, positive or negative emotions resulting from the interaction, positive word of mouth, switching intention, as well as ethical concerns. The post-interaction experience can influence guests' decisions to engage with the robot again, their loyalty to the technology, and their intention to adopt it in the future.

4 Future Research Agendas and Associated Theoretical Perspective

The proposed themes provide insights into "what we already know" from previous studies on anthropomorphic AI robots. One of the key aspects of this research is identifying the future direction that should be pursued, which can serve as a guide for future researchers to observe HRI, particularly in terms of design and anthropomorphic elements. The five major themes of the future research agenda align with the previously proposed research themes. The future research agenda, subsequent research questions, and several relevant theoretical perspectives are summarized in Table 1.

Table 1. Future research directions and questions

Themes	Questions for Future Research	Theoretical Perspective
Anthropomorphic Attributes	▪ How do various anthropomorphic features influence customer emotions such as anger, frustration, joy, or gratitude? ▪ How do anthropomorphic AI robots interact with human service providers like front desk staff, waiters, or flight attendants?	▪ Theory of Anthropomorphism; ▪ The Uncanny Valley Theory; ▪ The Computers Are Social Actors (CASA) paradigm
Service Contexts	▪ How do different types of tasks, such as functional versus hedonic, influence customer reactions to robotic services? ▪ How does the importance of these tasks, such as core tasks versus supporting tasks, affect customer responses?	▪ The Task-Technology Fit Theory; ▪ Hedonic and Utilitarian Motivation; ▪ Expectancy-Value Theory
Adoption Intention	▪ What additional factors, such as the robot's voice, personality, and cultural background, influence guests' attitudes and adoption intentions?	▪ Artificially Intelligent Device Use Acceptance (AIDUA); ▪ Technology Acceptance Model (TAM); ▪ The Service Robot Acceptance Model (SRAM);
Interaction Experience	▪ How do robots that closely resemble humans impact people's attitudes and emotions in unique ways? ▪ How does cultural diversity impact perceptions and behaviors toward AI robots in different countries? ▪ How do gendered anthropomorphic features affect customers differently based on their gender? ▪ How can future studies assess the actual behavior of guests interacting with AI robots instead of solely relying on self-reported attitudes and intentions? ▪ What benefits does assessing actual behavior offer in understanding the true impact of AI robots on guests' experience?	▪ Social Exchange Theory; ▪ Human-Robot Interaction; ▪ Cognitive Appraisal Theory; ▪ The Usability, Social Acceptance, User Experience, and Societal Impact (USUS) framework; ▪ Customer-Robot Value Co-Creation

Themes	Questions for Future Research	Theoretical Perspective
Post-interaction and Ethical Considera-tion	■ How do human employees perceive and interact with their robotic colleagues? ■ What impact do robots have on human employees who work closely with them? ■ To what extent do robots enhance the capabilities of human employees and optimize organizational per-formance? ■ Are human employees worried about being replaced by their robotic colleagues, and does this concern re-sult in maladaptive workplace behavior? ■ How should different types of service robots be compared to understand their effects on consumer perceptions and behaviors? ■ How do recurring failures and subsequent recoveries affect consumer trust, satisfaction, and loyalty to-ward service robots and the companies that use them?	■ Social Response Theory; ■ Social Relationship Theory; ■ Compensatory Consumption Theory

5   Conclusion

The application of service robots in real-world settings still faces various dilemmas and skepticism from different groups. This indicates a broad scope for further research opportunities in this area. The results of this study can serve as an important milestone for future empirical research. The themes and theoretical foundations used by previous re-searchers can provide a starting point for further developing concepts and theories. The following research directions in this study are also useful for researchers interested in delving deeper into the concept of anthropomorphic AI robots. Many areas still have yet to be explored, presenting significant opportunities for future research in this field.

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Section 4: Artificial Intelligence & Marketing

Artificial Intelligence in Tourism and Hospitality Marketing – Nexus of Human and Nonhuman Practices

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Abstract. This paper discusses the nexus of human and nonhuman artificial intelligence (AI) -related marketing practices in tourism organizations in Finland, Lapland. The study explores the post experiences, current operations, attitudes and fears of tourism organizations towards AI and the role of AI technology as a nonhuman agent. In this practice-based research, the method used was qualitative inductive content analysis. The preliminary findings show the situation of human and nonhuman practices and the level of adoption of AI in tourism marketing operations. In addition, the findings address a relatively positive tone in attitudes and a strong interest in AI adoption in future marketing operations. These attitudes towards AI highlight the lack of knowledge - ignorance of necessary skills and resources, whilst fears are mostly related to data privacy issues. Additionally, the findings indicate that the risk of losing authenticity in the marketing content is experienced as a fear. However, AI is not seen as a threat to replace humans; rather, it is seen as a nonhuman resource to compensate for a lack of human resources in marketing and sales operations. According to the findings, there is a need to research the role of AI in marketing and thus create an efficient combination of human and nonhuman practices for sustainable marketing practices.

Keywords: Human and Nonhuman, AI in Tourism Organization, Sustainable Marketing Practices.

1   Introduction

This study aims to present the nexus of human and nonhuman artificial intelligence (AI) -related marketing practices in tourism organizations in Finnish Lapland. Recent advances in digital technologies have dramatically transformed practices in hospitality and tourism destinations [5, 8, 12, 18, 20]. For example, machine learning and large language models have opened up opportunities for using AI in marketing and sales operations [5, 15, 22]. As new technologies are increasingly being developed, a practice-based examination of the use of AI in marketing

and sales operations is warranted to demonstrate the relevance of AI in developing hospitable operations and sustainable marketing strategies in tourism destinations [3, 7, 12, 16].

As a popular peripheral and international tourism destination, Finnish Lapland offers an interesting example of a region where tourism is an important business. The tourism industry is highly developed, growing, and innovative by nature. The share of growing tourist overnights was over 2,2 million for 2022-23 [10]. The number is considerable compared to the inhabitants, 179,000 in the Lapland province.

This study exemplifies how practices in tourism and hospitality marketing develop due to the emergence of AI technologies. The study explores the combination of human and nonhuman roles and operations discussing the post experiences, current operations, and attitudes of tourism organizations towards AI, and the role of AI-enhanced technology as a nonhuman agent [1, 5, 7, 9].

The data was collected in April 2024 and reflects the situation in the tourism organizations of that specific time. It includes online observations of three chatbot operations and eight semi-structured interviews of destination management organization representatives and enterprises. The preliminary findings show that the destinations use and aim to adopt AI in marketing operations. However, using AI in marketing practices requires resources and well-considered decisions based on knowledge to evaluate AI's relevancy in defined marketing operations. Consequently, there is a need to research the role of AI in marketing operations and thus create an efficient combination of sustainable human and nonhuman practices.

2 Theoretical Background

The theoretical framework of this study explores AI-generated marketing practices utilizing a practice-based approach. It discusses and analyses the nexus of human and nonhuman AI-based marketing and sales as post, current, and future operational practices in the tourism organizations.

AI technology can be explained as a nonhuman's ability to imitate human reasoning to reach human intelligence [4]. It is reflected in machines' ability to simulate or mimic applied operations that could be defined as smart when executed by a human. As a technology, AI is multidisciplinary. It includes technical spheres, such as machine learning,

natural language processing, automation and robotics [14]. In this research, AI is considered a family of technologies that can recognize, analyze, act, learn and demonstrate advanced features of human intelligence in the problem-solving of marketing and sales operations [5, 13]. The practice-based approach in this study allows an exploration of the current operational practices and existing attitudes and fears toward AI, as well as the roles of humans and nonhumans in the setting. The practices are defined and applied as collectively shared templates of organized and recurring activities that both humans and nonhumans enact in order to perform marketing operations together [17, 19, 21]. Naturally, practices also change due to changing circumstances, here because of AI, a nonhuman enhancement.

3   Methodology and Method

For this study, the research methodology was integrated into a digital marketing study unit at Lapland University of Applied Sciences. Altogether, 21 Bachelor of Hospitality Management students collected data during their learning process and were supported by two senior lecturers throughout the study unit. The applied research study and the participation of students in particular was performed in accordance with the general principles of research ethics and good scientific practice.

The period of data collection took one week and was organized after the winter tourism high season in April 2024. The data collection concentrated on three chatbots and eight semi-structured interviews as Teams and email discussions. The humans of the data represent tourism organizations (coded as T), such as destination management organizations and tourism enterprises.

Thematic analysis was used to analyze the data and to form interpretations of the adoption, integration and plan in AI in marketing practices. The analysis focused on forming findings in four perspectives:

1. Post-experiences of using AI
2. Current operations with AI
3. Attitudes towards AI
4. Attitudes against AI and Fears for AI

4   Preliminary Findings

The findings show that 82% of respondents currently use diverse operations of AI to support their marketing practices. They saw many benefits of using AI in marketing processes. For example, AI can suggest ideas, keywords and structures for creating marketing content. It can help to recognize new phenomena, thus suggesting unique perspectives for marketing. Moreover, providing text jargon for project applications and reporting is mentioned as a benefit in current operations (T2, T7, T9-10).

The practices of AI implementation are explained as an ongoing process (T9). It is defined as testing the AI solutions that are assessed safe and suitable for the organization practices and technical architecture (T9). For example, the Adobe AI plug-ins include such elements (T9). Interestingly, the future of Enterprise Resource Planning includes attempts at AI integration as an ongoing development project (T8).

The findings show that AI-enhanced marketing practices require human and nonhuman collaboration in defining the roles and responsibilities of AI in marketing practices. Questions such as "How to start and count the resources in using AI?" (T2, T8) create a basis that organizations are pondering roles, resources and safety of AI even in a broader context, such as in defining an AI strategy for the organization.

Despite the generally positive attitudes toward AI (55%), the findings also emphasize opposite reactions, such as "AI is not our practice" (T11) and "AI provokes fears of safety" (T10). Remarkably, the attitudes against and fears are analyzed to be present when discussing the similitude of destinations' brands and AI's tone of voice (T7, T11). There is a fear that AI might cause a risk in marketing if the authentic message of the destination or company characteristic. "The challenge is in authenticity! While AI does not recognize the authentic data of the destination it generates, for example, deep-fake videos or photo manipulation that are based on wrongly combined data, such as a husky safari in the Midnight sun or utopian northern lights" (T7). However, the fear of compensating workplaces is not valid (T7, T10) because of mainly micro and small-sized organizations in the region.

5 Conclusions and Discussion

According to the preliminary findings, AI is capable of statistical learning and data classification. Although it is considered a beneficial tool in marketing operations, its ability to conceptualize and infer is still somewhat limited. Nevertheless, the resources of AI, such as its operations as a repetition-capable nonhuman, are seen as wise and relevant to enhance marketing practices. However, the practices, such as generating text jargon, expose AI implementation to organizations. Here, AI is not always considered a constant practice but rather a test-bed platform.

The attitudes against AI highlight the ignorance of necessary resources, such as competencies of AI and its implementation to practice. However, the positive tone of this nonhuman agent can create new roles in marketing practices. For example, AI can teach tourism organizations to renew their marketing processes by monitoring marketing process scalability. Moreover, AI can analyze customer inquiries by delivering live information of possible risks concerning service disappointments but also the joy of customer satisfaction [6]. It is relevant to address the organizations' interests when evaluating and encouraging their possibilities for AI use.

Despite several modelling attempts, it can be argued that AI cannot replace a sensitive and cognitively gifted human [2, 24]. The fear of losing jobs because of AI is not a relevant threat, but the lack of competence-capable, empathic humans is. Indeed, the fears about implementing AI concern data privacy and authentic tone of voice elements.

Therefore, to support employees' understanding and practices, organizations should create instructions to guide and regulate the use of AI. In shaping the future of tourism and hospitality, it is relevant to continue researching the critical roles, responsibilities and practices of humans and nonhumans in technology-related settings [1, 7, 20]. AI can be considered a driver for sustainable growth when implemented and led by humans [23]. As the options for AI are increasing rapidly, tourism and hospitality organizations need to make well-considered and preferably research-based decisions regarding AI implementation. It can be argued that there is potential for the controlled use of AI as one driver in marketing operations when creating sustainable marketing strategies for tourism companies [5]. This will create value for all – companies, employees and customers in creating positive implications like enhanced employee and customer experiences.

Tourism destinations must understand the fundamental change [2] in the dynamics of tourism and hospitality marketing practices that the AI is constructing. It can be argued that the role of AI is to create ideas and generate discussion of practical prospects for a more sustainable destination experience [6]. However, one needs to remember the insight of AI as an emerging multispecies agent. Instead of being afraid and considering nonhumans as enemies, we humans should face and lead them in co-creating value for tourists and the tourism and hospitality business. Our responsibility is to develop human relations with nonhumans to avoid an AI technophobia-related tagline: "Fear of tech take over" (FOTTO) [11].

As already agreed, in spring 2025, the research and the data collection will be repeated to evaluate the use of AI in marketing and to contribute to the responsible practices in tourism destinations of Finnish Lapland.

6   Acknowledgment

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Toward a Framework for Destination-specific LLM and GenAI Adoption by Taiwan's Tour Operators

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Keywords: Generative AI, Tour Operators, Value Co-creation, Destination.

1 Introduction

1.1 The emerging trend of Generative AI adoption in tourism in Taiwan

Since the launch of OpenAI's ChatGPT in late 2022, which is based on the generative pre-trained transformer (GPT) 3.5 large language model (LLM), artificial intelligence (AI) has gained increasing public awareness. In June 2024, Computex attracted over 85,000 visitors from 162 countries to Taipei. Nvidia's CEO, Jensen Huang, sparked widespread enthusiasm for GenAI innovation, reinforcing the transformative potential of this disruptive technology across various sectors. Lion Travel, Taiwan's largest tour group, publicly announced the intention to integrate GenAI into their operations, emphasizing the potential for innovation and investment in the travel sector. This demonstrates how GenAI is being positioned not just as a tool for efficiency but as a driver of industry-wide growth for Taiwan tourism, where the sector confronts critical challenges such as labor shortages and fosters a technological revolution.

Given these dynamics, a key question arises: how do Taiwanese tourism stakeholders perceive the potential of GenAI as a catalyst for business growth and digital transformation? To address this, the principal investigator has employed an inductive approach, gathering insights on GenAI adoption since June 2024. The study leverages Actor-Network Theory (ANT) to analyze tourism innovation, specifically examining GenAI's role in transforming the travel industry. The findings are expected to provide a roadmap for integrating GenAI into tour operations,

offering actionable insights for tourism practitioners and government agencies to elevate the industry at destinations.

2 Literature Review

2.1 The prospective and hindrance of adopting GenAI in travel businesses

The potential of GenAI in tourism has been widely acknowledged by both academics and industry professionals [1]. Scholars have explored its application across various stages of the travel experience—before, during, and after the trip [2]. When effectively integrated, GenAI-powered chatbots can significantly improve customer experiences, enhance engagement, and reduce operating costs [3]. By leveraging deep learning, travel companies can optimize resources, personalize travel experiences, target specific market segments, and deliver higher-quality service products [4].

However, despite the promise of GenAI, there is uncertainty regarding whether traditional travel agencies—offering varied levels of service—are ready to integrate this technology into their day-to-day operations. While global online travel agencies (OTAs) like Expedia and Booking.com have embraced chatbots to enhance the customer journey [5], conventional agencies often emphasize personalized, human-driven services. This raises the question of why some traditional agents hesitate to adopt advanced technology like GenAI [6].

Research suggests economic concerns and perceived value-for-money are common barriers to adopting smart tourism technologies [7]. Therefore, a top-down approach, driven by a shared vision and a clear understanding of the needs of operators, may be required to encourage the widespread adoption of GenAI and other technologies. This approach could help traditional travel agents upgrade their capabilities to remain competitive in an evolving market.

2.2 Digital transformation of travel industries

Scholars have proposed the concept of a smart tourism ecosystem, where destinations incorporate advanced technologies to enhance the tourist experience. However, to optimize offerings, destinations need access to data on tourist behavior, which can help improve targeted

marketing and create superior visitor experiences. Despite these benefits, tourists often express concerns about data breaches and privacy issues [8]. Additionally, the increased reliance on technology may diminish the personal interactions between hosts and guests, potentially impacting the destination experience from the visitor's perspective [9]. This shift may significantly alter the industry's structure, requiring tour operators and service providers to rethink how they engage tourists and deliver unique experiences.

For tour companies, adopting advanced technologies like GenAI necessitates reconsidering the human-machine interface [10]. The focus should be on designing workflows that integrate employee support and technology in ways that enhance guest experiences and strengthen the company's brand. For instance, determining when and how employees should be assisted by GenAI can create more value for guests and improve overall service. Nevertheless, tourism employees may have a conflicting attitude as low-skilled and repetitive tasks are increasingly being replaced by AI, reshaping the job landscape [11].

2.3 Actor Network Theory and Business Model Innovation in Tourism

Scholars frequently turn to the actor-network theory (ANT), developed by sociologist Bruno Latour, to better understand the complex network involved in tourism innovation. ANT posits that both human and non-human factors are "actors" in forming tourism innovation networks, emphasizing the role of technology as non-human actors shaping new development [12]. The components may include involved actors (tourists and suppliers), non-human objects (resources and technologies), and no interaction (tourismscapes). On the other hand, it also highlights that tourism intermediaries should be considered actors, together with travel consumers, destination resources, and other service providers [13].

At the same time, business model innovation (BMI) is also considered the mediator connecting emerging technology with company operations. Businesses are recommended to explore from strategy, innovation, and entrepreneur perspectives. This includes resource-based, knowledge-based, and dynamic capabilities-based views to align with operational goals and market demands [14]. ANT and BMI offer complementary insights into how tourism innovation emerges toward technological integration and competitive advantages.

3 Methodology and Taiwan as the Study Site

3.1 Government advocacy for GenAI Adoption in Taiwan

Taiwan is identified as an ideal environment for research on the adoption of GenAI in tourism innovation. Its "AI Cabinet," as the government is nicknamed, has prioritized the integration of GenAI in both education and industry, fostering an environment ripe for studying the phenomenon. For example, the Ministry of Education has advocated the integration of GenAI tools into classrooms at all educational levels. These government-backed campaigns and targeted funding have further created fertile ground for GenAI-driven digital transformation, positioning Taiwan as one of the global pioneers in the GenAI movement.

3.2 A qualitative investigation into tourism stakeholders' perspective

The researchers explore the tourism stakeholder perspective with an inductive approach. The data collection period starts in June 2024 and includes secondary data collection, field observation, and in-depth interviews. This study responds to the research gap where there is a lack of diversity in research from the perspectives of local communities and small and medium-sized tourism enterprises [15]. Table 1 presents the up-to-date informant profiles for the in-depth interviews. Given the exploratory nature, the interview questions surround the business model themes such as customer identification, value delivery, value co-creation, and value capture.

Table 4. Informant Profiles

No. Organization Type	Position	Interview Duration
01 Tourism Authority	Senior Manager, Planning	1h 26m
02 GenAI Education Provider	Sales Director	2h 50m
03 Travel Agent (Large)	Senior Manager, Events	2h 16m
04 Tourism Scholar	Assistant Professor, AI	1h 45m
05 Tourism Association (Niche)	Chairperson	1h 22m
06 Tourism Association (Broad)	Senior Manager	0h 52m
07 Travel Agent (Large)	Senior Manager, Technology	1h 18m
08 Travel Agent (SMEs)	General Manager	3h 38m
09 Tourism Association (Niche)	Chairperson	1h 23m
10 Travel Agent (Large)	Senior Tour Planner	1h 44m
11 Travel Agent (SMEs)	General Manager	1h 16m
12 Travel Agent (SMEs)	Tour Operations Coordinator	1h 19m
13 Travel Agent (SMEs)	Marketing Manager	0h 51m
14 Market Analytics Provider	General Manager	1h 06m
15 Tourism Innovation Hub	Chairperson	2h 34m
16 Travel Agent (SMEs)	Sales Representative	1h 32m
17 Travel Agent (Large)	Senior Manager, Sales	1h 11m
18 Hotel (Leisure)	General Manager	4h 33m
19 Destination Tech Solutions	Manager, Strategic Research	2h 23m
20 Performance Group	Tour Manager	1h 21m
21 Travel Agent (Large)	General Manager, IT	1h 30m
22 General Sales Agent (Airline)	Senior Manager	1h 04m
23 Travel E-Commerce Platform	Product Manager	1h 36m
24 Corporate Training Service	General Manager	1h 34m

4 Preliminary Results and Future Directions

4.1 The tourism stakeholders' perspective

The preliminary findings are presented through a conceptual framework that explores tour operators' GenAI adoption with the context of destination-specific LLMs (see Fig. 10). The vertical axis represents the operand resources, encompassing tangible elements, including GenAI instruments as non-human actors and human actors, such as tourists and

destination communities. In contrast, the horizontal axis represents operant resources, which include knowledge generated by LLMs and the professional expertise and capabilities of intermediaries. It is proposed that a destination-specific LLM will enable value co-creation among all actors involved. However, as GenAI tools continue to evolve, the roles of tourism intermediaries are expected to change alongside with the sophistication of LLM capabilities. There is an ongoing discussion regarding which tasks should be fully replaced by AI-generated services, and which should be supported by various forms of AI-assisted services (i.e., supplemented, mediated, or facilitated) throughout the tourism value chain.

Also, while most informants acknowledge the industry-wide potential of GenAI adoption in tourism, they noted that travel agents as SMEs in nature, may lack the financial resources to attract investment in collecting the data and building a destination-specific LLM. To address these challenges, it is suggested that tourism authorities, third-party travel associations, or technology platforms may take the lead in developing destination-specific LLMs that benefit both the travel industry and tourists. Collaborative initiatives, such as centralized LLM infrastructures, could democratize access to these technologies and ensure equitable benefits across the tourism ecosystem, fostering innovation and enhancing value for both the industry and tourists.
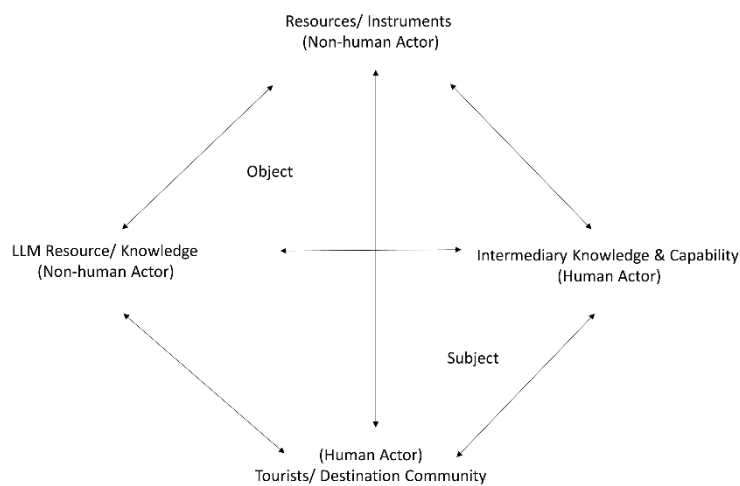
Fig. 10. Conceptual framework: tour operators' GenAI adoption with Destination-specific LLM

At the same time, ethical issues and privacy concerns arise when sensitive personal data, such as location, personal preferences, and purchasing behaviors, are collected to enhance the travel experience throughout GenAI systems. A more responsible and balanced approach is needed, prioritizing user privacy and nurturing trust among all stakeholders in the tourism ecosystem.

4.2   Future Research Directions

This working paper will continue to employ an open coding process to analyze the interview transcripts and thick data collected from the field. The primary objectives are to identify the key information required for developing destination-specific LLMs that effectively benefit tourism stakeholders, and outline a practical roadmap for tourism intermediaries navigating the era of GenAI adoption. Additionally, it will focus on developing the sustainable public-private partnership and explore the plausible business model with the framework, including the economies of scope and workflow for human-machine workforce dynamics, ensuring practical and sustainable integration into tourism operations.

Future research could investigate and evaluate the effectiveness of GenAI in enhancing tourist experiences with and without tourism intermediaries across different regions and cultures. It will be critical to address the privacy and ethical concerns so as to ensure the responsible development and application of GenAI tools in tourism.

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AI transparency and tourists' decision-making

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Abstract. The tourism and hospitality industry is increasingly adopting technologies such as Artificial Intelligence (AI) to offer personalized services. However, the opacity of AI algorithms raises concerns about the lack of transparency in how these recommendations are generated, potentially undermining tourists' autonomy. This research aims to investigate how transparency in AI-driven recommendations influences tourists' decision-making and purchase intentions. Drawing on theories of human autonomy, we hypothesize that tourists will prefer AI-recommended travel options that offer greater transparency about the decision-making process. Across multiple studies, we explore the relationship between AI transparency and tourists' evaluation of recommendation helpfulness, considering factors such as the role of transparency in AI versus human-generated suggestions. Our findings suggest that transparent AI recommendations enhance tourists' autonomy and empower them to make more informed decisions. The results also indicate that increased transparency leads to higher purchase intentions, even when user-generated ratings vary. This study contributes to the growing body of literature on AI ethics in tourism by emphasizing the importance of transparency in fostering trust and improving tourists' decision-making experiences.

Keywords: AI recommendation, Transparency, Tourist autonomy.

1   Introduction

Tourism and hospitality industry actively adopt and invest in technology to digitize businesses, utilizing tools such as artificial intelligence (AI), machine learning (ML), and virtual reality (VR) [1]. Specifically, with the recent remarkable leaps in generative AI technology, companies are creating new personalized services that were not easily executed before [1]. Naturally, tourists' information search behavior has significantly shifted to online channels from traditional offline sources

[2]. Against this backdrop, online travel agencies are competitively introducing AI services [3].

However, the opacity of AI algorithms is considered a technological issue [4], leaving tourists uncertain about why and how product options are presented on their screens. Consequently, these algorithms function as 'black boxes' to users, posing risks of potential misbehavior by AI [4, 5]. To address the challenges posed by opaque AI, there have been calls for greater transparency from both governmental bodies and academic discussions [6, 7].

Despite the introduction of AI recommendations and the emphasis on transparency in AI commercialization, research on AI in tourism remains in its early stages. Therefore, this empirical study aims to examine how tourists interact with AI in their decision-making processes. Through multiple experiments, we seek to identify tourists' behavioral patterns regarding the impact of transparent AI-based information and explore the psychological motivations behind these decisions. In doing so, we aim to explore how and why tourists are inclined to AI recommendations that are transparent from the perspective of human autonomy.

2 Literature review and hypotheses development

2.1 Opacity and transparency of AI travel recommendation

As Artificial Intelligence (AI)-powered tourism services become the industry standard, the implications of such technology have been largely overlooked. Despite the convenience these services offer, tourists often have a limited understanding of how AI generates tourism information and services across various online platforms. More frequently, tourists are deceived into believing that AI-recommended services were hand-picked by human staff [8], therefore, tourists are uncertain about why and how the information has been provided. Such consequential opacity trait of the AI algorithm has been defined as humans' inability to fully understand AI's decision-making process [4]. Hence, the algorithm works within AI and is depicted as a black box to humans [4], increasing our blind reliance on it, particularly, if the data utilized by AI lacks proper supervision [9].

Recognizing that the opacity of AI's decision-making is one of the primary challenges in utilizing the best use of AI technology, the regulation for AI-based personalized travel services has been proposed [6, 7]. Under such efforts, transparency becomes a crucial concept in the regulation of AI usage [10]. Transparency allows making implicit values explicit [10], such that it reifies data transparency (i.e., how and why certain data is collected for which purposes, [11]) as well as AI algorithm explainability (i.e., how decisions made by an AI system, [9]). The demands on transparency in tourism and hospitality are increasing along with the industrial digital transformation, where the majority of tourists are expected to make decisions with AI-based recommendations and guide services throughout their journey [10, 11].

2.2 Transparency and tourist autonomy

To understand the impact of transparent information on tourists' decision-making, we propose that tourists' autonomy is a key motivator for demanding transparency in AI recommendations. Human autonomy, often discussed from ethical and psychological perspectives, is considered fundamental to human respect and psychological well-being [12, 13]. In its broadest sense, autonomy refers to 'self-rule', or the ability to act freely and make their own choices [14]. Building on this, we operationalize tourists' autonomy as the individual's ability to control their decision-making for their trips.

As technology advances, there has been debate over whether such technology (e.g., AI, robots, machine learning) could eventually undermine human autonomy. For example, a dystopian perspective raises concerns that AI systems may manipulate decision-making by pre-filtering options and acting as subtle 'nudges' that guide our choices [15]. On the other hand, human autonomy can also be enhanced through the provision of relevant information and interactive tools that improve decision-making competencies [15]. From this perspective, transparency becomes an essential enhancer of tourists' autonomy, moving beyond 'take it or leave it' choice options [12].
In the context of AI recommendations assisting tourists with travel planning, data transparency and algorithmic explanations can empower tourists by helping their decision-making and helping them predict outcomes [9]. In other words, when more explicit information is available, tourists can better reason and evaluate their options based on personal criteria. Tourists equipped with such intentional information make

more informed decisions aligned with their plans and expectations. Therefore, considering human nature's inherent drive for autonomy and the anticipated positive effects on decision-making, the transparency of AI recommendations should incline tourists toward choosing transparent options. Based on the theoretical framework, we propose the following hypotheses, as illustrated in Figure 1:

Hypothesis 1 (Study 1a, 1b): *Tourists' purchase intention for an AI-recommended travel option will be stronger when the option provides greater transparency about how the recommendation was generated, compared to an AI-recommended option with limited transparency, regardless of the type of travel product.*

Hypothesis 2 (Study 2): *The increase in purchase intention for the AI-recommended travel option with greater transparency (compared to limited transparency) will be mediated by tourists' evaluation of the helpfulness of the recommendation.*

Hypothesis 3 (Study 3): *Tourists' purchase intention for the recommended travel option will be stronger when it presents greater (vs. limited) transparency particularly when the source of recommendation is AI than humans.*

Hypothesis 4 (Study 4): *Tourists' purchase intention for the recommended travel option will be stronger when it presents greater (vs. limited) transparency particularly when users perceive AI as machine than human.*

Hypothesis 5 (Study 5): *Tourists' purchase intention for an AI-recommended travel option will be stronger when the option provides greater transparency, even when the recommendation differs in user-generated online ratings (e.g., high, mid, or low star ratings).*
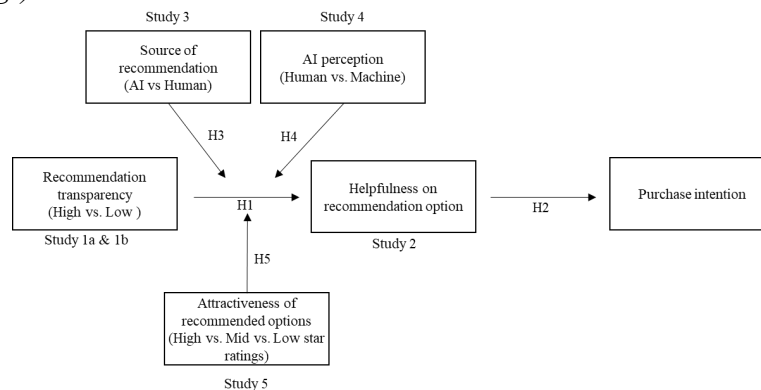
Fig. 11. Research model

3   Methods

3.1   Overview of studies

Table 1 summarizes the study methods and results. All studies were conducted using online, scenario-based experimental designs, with data collected from an online panel via CloudResearch to ensure high-quality responses. Participants reviewed stimuli on recommendations (car rental, tour activity) that differed in transparency level (i.e., how was recommendation made), source of recommendation, and user ratings. Then, hypothetical scenarios were given to measure their purchase intention for each experiment.

4   Discussion and implications

Our findings suggest that people prefer transparent information when making decisions based on AI-generated recommendations. This preference arises because users perceive transparent AI as helpful in their decision-making process. We theorize that this effect is linked to tourists' sense of autonomy, as transparency enhances their ability to make independent decisions. Even if options are recommended by AI, users feel empowered to evaluate the provided choices critically. Additionally, regardless of the source of the recommendation, the results indicate that transparency effects are considered more important in decision-making. However, how users perceive AI in travel planning plays a crucial role.

This study contributes to the growing body of AI research in tourism and hospitality by offering causal explanations for a relatively underexplored field of AI ethics perspective [16]. Understanding preferences for AI transparency may provide practical insights for designing more effective AI travel recommendations and addressing ethical considerations in policy regulation, which is a key factor in planning personalized tourism services. Particularly, drawing on the importance of transparency in AI commercialization, the empirical study investigates the tourists' communication with AI in decision-making.

Table 5. Overview of studies

Study	IV	DV	Results	Hypotheses
Study1a: *Rental car option scenario*	Recommendation transparency (low vs. high), Within-subject 105 US adults (M_{age} = 40.55, SD = 1.26, 55.2% female)	Rental car option purchase intention	One-way ANOVA with repeated measures: $F(1,103) = 70.19$, $p < .001$, $\eta^2 = .405$.	H1 supported
Study1b: *Tour activity option scenario*	Recommendation transparency (low vs. high), Within-subject 117 US adults (M_{age} = 49.94, SD = 1.37, 53% female)	Tour activity option purchase intention	One-way ANOVA with repeated measures: $F(1,115) = 30.49$, $p < .001$, $\eta^2 = .210$.	H1 supported
Study2: *Rental car option scenario*	Recommendation transparency (low vs. high), Mediator: recommendation helpfulness, Between-subject 106 US adults (M_{age} = 44.62, SD = 1.52, 53.8% female)	Rental car option purchase intention	PROCESS Macro (Model #4): Indirect effect: $\beta = .30$, SE = .17, 95% CI: [.003, .669].	H2 supported
Study3: *Rental car option scenario*	Recommendation transparency (low vs. high), Moderator: source of recommendation (AI vs. human) between-subject, within-subject on transparency order, 510 US adults (M_{age} = 45.06, SD = 1.39, 52.2% female)	Rental car option purchase intention	Mixed-model ANOVA: $F(1,506) = 2.77$, $p = .097$, $\eta^2 = .005$.	H3 not supported
Study4: *Rental car option scenario*	Recommendation transparency (low vs. high), Moderator: AI perception (machine vs. human) between-subject 492 US adults (M_{age} = 40.96, SD = 1.32, 54.5% female)	Rental car option purchase intention	PROCESS Macro (Model #1): $\beta = -.01$, SE = .00, $t = -2.03$, $p = .043$, 95% CI [-.017, -.000].	H4 supported
Study5: *Rental car option scenario*	Recommendation transparency (low vs. high), Mediator: recommendation helpfulness, Moderator: online review rating (low vs. mid vs. high) between-subject 368 US adults (M_{age} = 44.51, SD = 1.38, 59% female)	Rental car option purchase intention	Two-way ANOVA: $F(2, 362) = .86$, $p = .424$, $\eta^2 = .005$.	H5 supported

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AI in tourism research: are black box models THAT strange?

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Abstract. Artificial intelligence (AI) advancements have brought a large spike of interest in the tourism academic community. Yet only a handful of literature contributions have used AI applications for research. We argue that the disparity between the interest in AI applications and the apparent hesitance to use AI in research is related to the "strangeness" aspect of the black-box algorithms. In our contribution, we explore the AI strangeness effect using the topic modeling with large language models (LLMs) as an example and propose ways to improve AI acceptance in tourism research practice.

Keywords: Neuromarketing, staged destination, realists, postmodernists, heart rate variability.

1 Introduction

Recent advancements in artificial intelligence (AI) brought a large spike of interest in the tourism academic community. For instance, Tourism Management and the Journal of Travel Research have published 26 papers dealing with artificial intelligence; out of these papers, only 5 were actually using artificial intelligence for research; the rest were investigating AI applications used by others, mostly the issues related to AI adoption: perceptions of travelers of AI recommender systems, AI usefulness in management, perceptions of robots and autonomous vehicles, etc. Similarly, possibly the largest progress in AI, the large language models (LLMs), have inspired 53 papers in Tourism Management and the Journal of Travel Research. Yet, only five of these papers used LLMs for studies, while the majority researched the implications of LLM use by travel planners and tourists. Moreover, while many specialized LLMs have been created to aid academic research in many fields, such as medicine, we are familiar with only one

tool created to aid tourism researchers [1] used in a single application by researchers other than the tool's authors [2].

The same observations can be made about other advanced data mining tools, which slowly percolate into the tourism literature. This includes, for instance, social network analyses, machine learning, genetic algorithms, fuzzy sets, neural networks, and others. In this paper, we aim to deconstruct the issue of sparse use of AI, including data mining and LLMs, in tourism research through the lens of trust in progressively opaque algorithms and model explainability. We use examples from LLM applications.

The rest of the paper is written as follows. First, we introduce the literature discussing the "black box" algorithm acceptance problem to build the opacity – justification – unpredictability – strangeness framework. Next, we apply this framework to accepting three topic modeling algorithms in tourism literature: LDA, BERTopic, and GPT. Next, we cross-compare the performance of these algorithms to demonstrate that the most accepted algorithm, LDA, is, in fact, the least accurate. Finally, we discuss our findings from the Black Box problem perspective.

2   Black Box problem

The black box problem [3, 4] refers to a lack of trust in artificial intelligence (AI) algorithms. Brożek et al. [5], in a controversial paper discussing the replacement of a judge with an AI for simple legal proceedings, deconstructed the black box problem into four issues:

- *opacity*: a limited understanding of the process by which the conclusions were derived;
- *justification*, inability to explain a reason for a specific outcome;
- *unpredictability*, arising from humans' aversion to "surprises"; and
- *strangeness*, arising from humans' aversion to "soulless" algorithms.

Notice that the issues escalate from those based on the rational ones (indeed, the functionality of the black-box algorithms is opaque) towards the emotional ones. This inclusion of the emotional component makes dealing with the black box model problems gradually more complex. Indeed, [5] argues that contrary to common beliefs, the opacity

problem is easy to deal with: even though the underlying concepts of an algorithm may be extremely complex, simplified explanations are readily available. Indeed, even though the challenge of explaining LLMs' basic components, such as encapsulation, transformers, or attention mechanism, is high, a popular simplistic explanation "an LLM generates answers by predicting the most likely sequence of words based on patterns learned from vast amounts of text data during training" creates a sense of understanding.

Regarding the second issue with the justification of model outcomes, it is indeed hard, if not impossible, to provide justification for black-box model results in a classical sense of delineating the steps leading the model to convert raw data (for instance, ChatGPT prompt "Calculate 1+1") to a response ("1 + 1 equals 2"). However, the justification problem can be resolved in a way similar to the model opacity issue. A new field of "Explainable AI" [6, 7] is tackling the justification problem by developing special applications explaining how a black-box solution was achieved. For example, several methods have been theorized to help in understanding GPT results, including GPT models trained on explanation data [8]. The unpredictability problem is related to the first two. Once a person can "understand" the way AI functions and how it has arrived at a particular solution, it becomes easy to justify accepting it.

According to [5], the most important problem in accepting AI as a decision-maker is the *strangeness* of the very fact of accepting the decision made by an AI as opposed to a human. Authors explain the term "strangeness" as the unwillingness of humans to accept the very way decisions are made. For instance, one can easily accept the decision to interpret a string of tokens/probabilities "pool (0.026); hot (0.02); water (0.018); spring (0.017); time (0.011)" (a real-world example of a word-topic matrix returned by an LDA model), as a "hot spring visit" since the decision-making process of an analyst is seemingly transparent and presumably based on the expert knowledge of the destination (Volcano Arenal National Park). At the same time, an identical decision that a list of 5000 reviews of the destination contains this topic, made by an AI algorithm, is not well accepted due to the irresolvable difference in the way this decision is made.

Applied to the use of AI in scientific research, the strangeness effect is in accepting the results of analysis suggested by an AI as opposed to a human investigator. The authors argue that the critical issue here is

the "folk psychological conceptual scheme" that the decision-making should be done only by real people, "equipped with rational minds and free will".

3   Case study: comparison of ChatGPT, BERTopic, and LDA performance

We argue that the acceptance of novel machine learning algorithms is primarily driven by the "black box problem" implications rather than the factual algorithm performance comparison. To support our point, we compare the performance of three machine learning algorithms used for topic modeling: Dirichlet Allocation (LDA) [9], BERTopic [10], and GPT 3 Turbo [11]. These black-box models have been referred to in tourism literature, however in different capacities. LDA and, to a lesser degree, BERTopic have been used as analytical tools. Meanwhile, GPT (and, especially, its variant ChatGPT, specifically fine-tuned as a conversational agent), has almost exclusively been used as an example in AI acceptance studies.

Table 6. Datasets.

Data Origin	Platform and data	N documents, mean and median N words
Comments, Li Ziqi agro-tourism videos	YouTube - Comments	N 444, mean 17.2, median 10
	Weibo - Comments	N 7171, mean 9.7, median 6
Discussion of travel to Corcovado nat. park, Costa Rica	TripAdvisor - Titles	N 618, mean 4.9, median 4
	TripAdvisor - Text	N 618, mean 130.6, median 78
Discussion of travel to Arenal Volcano, Costa Rica	TripAdvisor - Titles	N 13,582, mean 4.1, median 3
	TripAdvisor - Text	N 13,582, mean 79.1, med. 60

We applied all three models as topic modeling tools to six textual datasets extracted from TripAdvisor, YouTube, and Weibo social media platforms. Table 1 lists the main characteristics of these datasets. A detailed description can be found in Anonymous (2025).
Hence, the quality of 18 topic modeling results (six datasets x three models) was manually evaluated. Two raters carefully validated the results of topic modeling. The raters were offered a randomly selected sample of 100 documents for each simulation for a total of 1800 documents. They were asked to provide their agreement with the algorithm-

designated topic name for each of the documents. The interrater agree-ment (IR) measure was used on a sample of data to confirm manual validation quality and was found to be acceptable (IR = 0.82). Table 2 presents the percentage of documents with correctly identified topics.

Table 7. Percent of correctly identified topics in six datasets/three methods combinations.

Dataset	% correctly identified		
	LDA	BERT	GPT
YouTube, Li Ziqi	59%	80%	86%
Weibo, Li Ziqi	56%	60%	82%
Corcovado, titles	67%	75%	89%
Corcovado, reviews	54%	90%	84%
Arenal, titles	67%	54%	96%
Arenal reviews	63%	89%	87%

For most datasets, LDA was the worst-performing model regarding the percentage of correctly identified topics (based on a human rater's judgment), and GPT was the best-performing model.

4   Discussion

We argue that the core of the GPT topic modeling black-box problem relates to the strangeness aspect. The Latent Dirichlet Allocation model has been widely accepted as a valid topic modeling tool, becoming a common instrument for tourism academics. Indeed, over 50 papers that used LDA have been published in Tourism Management / Tourism Management Perspectives alone. Notably, LDA is a complex genera-tive model that returns probabilistic results in the form of a list of terms that further require human interpretation. Further, the model is known for problems with results robustness if not well tested. These features make LDA susceptible to three out of four Black Box Model problems: opacity, justification, and unpredictability.

Another seemingly accepted in tourism literature topic model, BERTopic, is even more challenging in terms of its opacity, justifica-tion, and unpredictability. BERTopic is an extension to a large lan-guage model BERT. BERTopic uses pre-trained transformer models to generate high-dimensional embeddings for text documents. These em-

beddings capture documents' semantic information. Further, the embeddings are clustered into groups of semantically related documents. A human "investigator-in-charge" should then interpret the clusters in terms of the document topics. Interestingly, a version of BERTopic, specifically trained on travel-related data, has been developed [12] but, unfortunately, is yet to be accepted by a larger tourism research community.

Notably, a human investigator is a key element in both the LDA and BERTopic topic modeling process. This feature makes analysis with both models similar to more familiar tools in a statistical toolbox, eliminating the AI strangeness issue.

Compared to LDA and BERTopic, GPT seemingly excludes humans from decision-making, returning a final list of topics without turning to the researcher's expertise beyond the initial prompt. That makes GPT extremely "alien". Further challenging the notion of AI strangeness, GPT is not unknown of "hallucinating", presenting incorrect information as if it were a fact. Notably, the analytical ability of GPT models is an emergent capability not enabled by model design. Indeed, GPTs are trained on the tasks of predicting the next token in a sequence. The model architecture allows it to generate authoritative statements and, in the case of the ChatGPT, to engage in a productive dialog with human users. This also means the model is optimized for linguistic rather than analytic abilities. We argue that this strangeness is the leading factor limiting analysis with generative LLMs such as ChatGPT in tourism research.

Architecturally, BERT is not capable of text generation. However, this seemingly important drawback allowed it to be trained to predict the tokens based on both the left and right sequences, making the model significantly more context-aware. Numerous models based on BERT or its variants have been pre-trained for specific tasks: topic modeling, sentiment analysis, name entity recognition (NER), question answering, text summarization, translation, and many others. Many of these tasks are essential for tourism data analysis, providing abilities to extract information on the points of interest, businesses, aspect-based sentiment, translation of reviews in languages other than the destination's, etc. Tourism literature is yet to unitize these capabilities.

ChatGPT is only the first generative LLM with emerging abilities extending beyond its primary function of text generation; more models

have been developed, and many more are coming. Hence, it seems unproductive to exclude the LLMs from the analytic toolbox. However, we suggest that accepting AI as a research tool is impossible without reducing the strangeness component of the Black Box problem. In our case study, we attempted one simple approach: human-rater validation of the GPT-generated topics. Despite the simplicity, researchers frequently omit this step. Meanwhile, this validation not only creates trust in GPT results but also eliminates the strangeness problem by returning the human researcher as a final decisionmaker. A wider integration of human judgment into AI-driven analysis bridges its gap with traditional research methods.

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Will digital technologies and AI automate hospitality jobs?

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Abstract. Looking at most of the latest news and research being published, it would seem that digital technologies, and especially AI, are ready to automate most jobs, even in the service industry. However, the reality seems to be far from this situation, as very few jobs have actually been replaced by AI and robots. In this contribution, we analyze the reasons for this situation by taking a closer look at the accommodation activity. We present an overview of how the process of automation is much more complex than expected. The main reasons are the complexity of most jobs in the hospitality industry, with many different tasks involved in each job, the change in processes needed in hotels in order to implement a new technology, the cultural change required, the costs involved in the process and the difference between when a technology is ready at the research and development level and when it is ready at the market level.

Keywords: Automation, AI, Digital Technologies, Robots.

1   Introduction

Since the launch of ChatGPT in November 2022, AI has been experiencing what could be called a golden age. Although ChatGPT and most of the technologies that have been released since then are Generative AI (GenAI) tools, a small subset of AI, the whole field of AI has been surrounded by hype. The promises around the capabilities of AI have exploded. In this sense, one of the areas in which there has been a growing debate in the media and in academia is that related to employment. It would seem that AI is ready or will be ready in the near future to replace almost all jobs [1].

The line of thought is that since technology is currently able to perform certain tasks that humans do, through evolution robots will get better and better and end up being able to do all human tasks. Based on the

perception that because of the amazing potential of modern technologies this time the impact of technology could be different [2].

In fact, historically technology has destroyed and created occupations and jobs. It happened with the automation of agriculture, with the steam engine and with the personal computer. In this case, AI and robots will affect the service industry and, more specifically, the tourism industry. In general, it is often considered that technology will be able to automate routine tasks and act as a complement to workers in non-routine tasks [3].

However, a closer and more in-depth analysis reveals that the situation is much more complex than it might appear initially. Jobs are complex, including many different tasks, permanent switching between tasks, and worker behaviors not explained in job descriptions [4]. In addition, most of the discourses related to automation through robots and AI refer to activities related with technologies such as business intelligence, virtual assistants/chatbots and intelligent avatars, which, at least in hospitality, do not really employ large numbers of people. Instead, jobs that are more common in hospitality, such as chambermaids, cooks and waiters have been examined far less.

In this article, we describe an analysis we conducted in hotels. We show that each job involves a large number of tasks. Although it is possible that a machine can automate some of these tasks, it is not feasible (at least currently or in the near future) to find digital technologies that will automate all the tasks required in any of the most common jobs in the accommodation activity. In the discussion we present a number of reasons that can also explain why the automation of jobs in the hospitality industry will not be as fast and straightforward as is sometimes said.

2　Methodology

For this research, we analyzed 24 four- and five-star sun-and-beach hotels situated in the Canary Islands. These hotels had an average of more than 300 rooms and approximately 130 employees. After the first 15 hotels we already reached the saturation point. However, we kept analyzing hotels since we had already scheduled the interviews. In each hotel, we asked the human resources manager about the distribution of employees through the hotel jobs. We then interviewed the head of each department as well as workers of each job in order to have a list of

the tasks allocated to the different jobs. We analyzed only the jobs located in the hotel, excluding the central services, because the number of employees in these central services was less than 10%.

To develop the list of tasks for each job, we first created a list based on three sources: the Spanish National Labor Agreement for Hospitality Companies, the O*NET database, and the European Skills, Competences, Qualifications and Occupations (ESCO) Classification of Skills, Competences and Occupations.

Most of the tasks in this initial list were specified at a very high level, making it difficult to understand what was being done or how automation might affect the true content of the jobs. For example, in the case of the housekeeper, one of the tasks in the initial list of tasks was "cleaning the rooms". This generic task includes several behaviors that needed to be explicitly addressed because they significantly differ from one another. Therefore, the initial list was reviewed with the head of each department and with the incumbents of the jobs (i.e., the household supervisor and the housekeepers in the previous case) in order to produce a more detailed list.

For example, the previously mentioned generic task ("Cleaning the rooms") was divided into three main tasks ("Cleaning and preparing the bathrooms of the rooms", "Cleaning and preparing the rest of the room", and "Making the beds") which in turn were found to have 11, 8 and 3 detailed tasks (e.g. "Emptying trash", "Cleaning and preparing the sink area in the bathroom", "Cleaning mirrors"). This is, the generic tasks in the initial list were divided into main tasks and each main task into a series of detailed tasks.

3   Results

In our sample, three jobs accounted for more than 60% of all hotel employees: housekeeper, waiter/waitress, and cook/cooking assistant. In total, more than 200 detailed tasks were identified in the operational jobs of the hotels. In the three jobs mentioned, a total of 109 tasks were identified. As an example of one of these cases, Table 1 shows the eight main tasks performed by waiters/waitresses.

Table 1. Main tasks carried out by waiters/waitresses

Preparing the service
Preparing the tables
Attending to customers
Providing table service
Managing service charges
Clearing and cleaning tables
Clearing and cleaning the restaurant
Other tasks

Table 2 shows the five detailed tasks into which the main task "Providing table service" is divided.

Table 2. Detailed tasks that form the task "Providing table service"

Taking orders
Communicating customer orders to the kitchen staff
Preparing beverages
Serving beverages
Serving food

Since a similar situation takes place for each of main tasks listed in Table 1, we found that waiters/waitresses develop a total of 31 detailed tasks in their job.

4   Discussion

Whether digital technologies and AI are used to replace all the tasks in a job or just some of them, the result will be similar: fewer workers will be needed to do the same amount of work.

However, our analysis shows that it is very complex to estimate how much of a job is automatable. Our results also show that the current risk of automation in hotels is relatively low, despite the major advances in digital technologies and AI in recent years. This low risk of automation is due to several factors.

The main reason, as we have shown, is that in the hospitality industry *there are many different tasks involved in each job*. This means that jobs are less routine than is commonly expected. The extent to which jobs are routine has been usually assessed globally (e.g., [5]). This

method does not reflect what workers really do in their jobs [6]. In addition, each task requires a different amount of time over the course of the day. It may be the case that tasks easier to automate take a small amount of time overall, while other tasks take more time throughout the day. Therefore, it is important to consider the amount of time that employees spend on the tasks of their jobs. If difficult to automate tasks consume a significant portion of the total work time, the risk of automation will be low. Also, we should consider that there are many implicit behaviors of workers that do not appear in the formal job descriptions [7]. Behaviors that workers do without even realizing it, but that can be complex to automate (e.g., in a hotel breakfast service, to set the chairs of a table correctly after guests have left). Finally, we found that in some cases the content of the jobs varies depending on service specialization, the use of outsourcing, or the size of the hotel.

A second reason is that in order to implement a new technology, *hotels need to change their processes*. Processes need to be redesigned to accommodate the technology being implemented. This redesign is not trivial. For example, implementing a cleaning robot in a hotel will likely require a series of changes in the room cleaning procedures. These changes are necessary because of both the guest's behavior (e.g., clothes and other objects thrown around the room) and to integrate the robot's activity with the housekeeper's tasks (e.g., the housekeeper should enter the room before the robot to check that there are no objects thrown around the room). In the same way, there is also a need for cultural change and training of the staff to work with robots and perhaps know how to diagnose the problems that may occur in the daily operation of the robot [8].

Another reason is that *today's hotels were not designed with robots in mind*. Behaviors that are very simple for humans can be very complex for a robot, such as walking on an uneven surface or cleaning a difficult to arrive space. In the future, there may be hotels that are designed entirely with the existence of robots in mind, so that they can operate at maximum efficiency and avoid certain issues that may be uncomfortable for robots, such as cramped spaces.

We must also keep in mind that there is a significant *difference between when a technology is ready at the research and development level and when it is ready at the market level*. The fact that a technology is ready does not mean that it can be implemented on a large scale immediately.

Of course, when discussing the implementation of digital technologies and AI, *economic issues* related to return on investment [9] and possible mistrust of how the technologies will perform in a production environment should be considered.

Finally, *the perspective of those that experience the technology*, the guests of the hotels, should also be considered. There may be some reluctance on the part of guests to use and stay in hotels where most of the work is automated by robots and AI [10]. There is also the case that the usability of the technology may not be the best, as the case of checkout in supermarkets shows, with some chains cancelling their deployment programs [11].

5   Conclusion

The main conclusion of this research is that digital technologies and AI are not yet replacing jobs in the hospitality industry, at least not to a significant level. In the case of the hospitality industry, when the analysis is done at the task level, our research confirms that until we have general AI capable of generating general-purpose robots, significant automation will not occur. The AI and robotic systems we have today can perform specific tasks. From this perspective, it is relatively easy to imagine a hotel, for example, having robots that clean the floors of the rooms. However, it is not so easy to imagine a scenario where cleaning a room requires a variety of different robots, each responsible for a specific task, or the possibility of having a single robot capable of performing all the tasks necessary to clean a room.

The main limitation of this study is that we have only analyzed the case of large four- and five-star sun-and-beach hotels, all of them situated in one destination. It would be necessary to analyze other types of hotels in order to understand if a similar situation happens across hotels.

Two last important points. First, it is difficult to predict technological progress, as demonstrated by the emergence of ChatGPT in 2022. Will we soon see generative robots that can play the same role as generative AI, learning to perform tasks by observing humans? Second, it is common to hear business representatives complain about the difficulties they face in managing human resources, due to issues such as absenteeism and difficulty in filling vacancies. These difficulties can drive the adoption of technologies that help overcome them.

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Section 5: Experience Reviews

Travel experience analysis based on visual concept modelling from travel photos

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Abstract. Understanding traveler preferences is crucial for effective tourism marketing and management. Traditional methods, such as surveys and questionnaires, often fall short in capturing detailed, large-scale data on travel experiences. While online travel photos contain rich information, they are underutilized due to limitations in analysis techniques. Existing approaches typically rely on textual data, such as textual metadata or machine learning to label photos, which may not accurately reflect the diversity of travel experiences, especially since photos with similar textual description can depict different experiences. This paper introduces a novel method for analyzing travel experiences by directly examining visual content through an advanced artificial intelligence-based technique called Concept Modeling. This method models photo content as travel concepts for subsequent analysis. We validate this approach with a case study of South Korea, utilizing a large-scale photo dataset. Our analysis aims to reveal variations in travel preferences among different groups and regions, providing insights that can help tourism marketers develop targeted materials and diverse travel packages to enhance traveler satisfaction and attract more visitors.

Keywords: Concept modeling, OpenAI, CLIP, travel photos, Flickr

1 Introduction

Research on travel experiences is a crucial domain within tourism literature, focusing on how individuals perceive, engage with, and reflect on their journeys [1]. Understanding travelers' experiences and preferences enables stakeholders to design and enhance tourism products and

services that better meet travelers' desires and expectations [2]. For instance, destination managers can improve the effectiveness of their marketing strategies by promoting travel experiences tailored to specific groups of travelers [3]. In a similar vein, tourism operators can customize travel itineraries and enhance service quality to align with travelers' preferences, thereby increasing engagement and satisfaction [4].

Analyzing travel experience preferences is a complex and challenging task due to the diversity and complexity, which cannot be effectively captured and analyzed using text-based data alone. For example, Fig.1a and Fig.1b depict beach scenes. Traditional approaches describe these scenes using words such as "beach," "sea," "tree," "sand," "sky," and "coast" for analysis. However, visually, the two scenes represent different travel experiences: Fig. 1a portrays a tropical beach ideal for swimming and relaxation, while Fig. 1b shows a beach more suited for sightseeing. Such distinctions can only be identified through direct visual content analysis, rather than relying on textual descriptions as in conventional methods [5]. To date, few studies have attempted to analyze travel experiences directly based on visual content to provide comprehensive insights into these experiences.

(a) The Mamanuca Islands, Fiji[1]   (b) Broome, Western Australia[2]

Figure 1: Beaches with different travel experiences.

This research proposes a novel method for the comprehensive analysis of travel experiences, based directly on the visual content of travel photos, addressing existing research gaps. Our method utilizes state-of-the-art advancements in computer vision, specifically Concept Modeling [6], which represents photo content as visual concepts for analyzing travel experiences. We aim to demonstrate the effectiveness of this method through a case study involving a large-scale dataset of travel photos taken in South Korea, a major tourism destination in Asia. Our analysis seeks to reveal travel experience preferences among various

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[1] https://www.planetware.com/seychelles/best-tropical-vacations-sey-1-12.htm
[2] https://www.coastandcountry.com.au/wa/broome

groups of travelers, and identify unique travel experiences available in different regions of South Korea. The method and findings will offer valuable insights for tourism marketing, facilitating the promotion of products tailored to specific traveler groups based on their travel experiences.

2   Literature Review

Prior studies on travel experiences have predominantly relied on qualitative data collected through surveys and questionnaires [7]. While these methods can provide in-depth insights into travelers' experiences, they are costly to implement and are limited by the number of responses and the comprehensiveness of the experiences captured. Consequently, alternative data sources, such as online reviews [8] and travel photos [9], are gaining attention due to their widespread availability and the richness of the information they contain. Among these, travel photos offer a significant advantage because they provide direct and vivid visual representations of travel experiences [9].
However, the potential of travel photos has not been fully realized due to the limitations of existing methodologies. Previous works have primarily focused on utilizing textual metadata (e.g., tags, titles, descriptions, comments) associated with these photos, which often fail to capture the semantic meanings contained within the images [10]. Other attempts have involved manually coding visual content [11], a process that is time-consuming and inefficient for large-scale studies. Recent advancements in computational approaches using deep learning have enabled algorithms to automatically identify travel concepts within photos [12]. Nonetheless, these techniques are often constrained by predefined concepts present in the training data, which can be costly to acquire for model training. To date, no prior studies have successfully analyzed travel experiences directly based on the visual concepts within travel photos, limiting the depth and breadth of insights obtained.

3   Methodology

The idea of Concept Modeling [6] is similar to that of topic modeling for textual data, which identifies topics or themes from text collections. Popular topic modeling techniques, such as latent Dirichlet allocation (LDA), Bidirectional Encoder Representations from Transformers

(BERT), and Generative Pre-trained Transformer (GPT) [12] were originally developed for text-based data, thus limiting their application potential to photos. Some attempts to apply topic modeling for photo analysis have been made [13]. However, they were applied to text-based data, such as textual meta data or labels predicted by other models, rather than directly to the visual content of the photos. This approach possesses similar limitations of deep learning model as discussed in Section 2.

Recently, a breakthrough in computer vision was achieved with the development of Contrastive Language-Image Pretraining (CLIP) by OpenAI[3]. CLIP transforms photos into vector representations, mapping each photo to a point in a semantic space, where photos with similar visual content are positioned close to one another. This mapping is highly reliable due to CLIP's training on a comprehensive dataset containing over 400 million image-text pairs from the Internet [14]. Visual concepts are defined as clusters of photos forming dense areas within this semantic space [6]. Visual concept modeling involves identifying these dense areas of photo clusters, with the number of such areas corresponding to the number of prominent concepts.

To identify these dense areas, an approach similar to that described by [15] is used, employing the hierarchical density-based spatial clustering of applications with noise (HDBSCAN) technique [16̶16̶]. The cluster centers serve as representative vectors of visual concepts and are visualized for analysis by selecting several representative photos from each cluster. Additionally, CLIP can map text into the same semantic space as photos via a text encoder. Text with semantic meanings similar to the visual concepts is located near the cluster centers, aiding in the interpretation of the visual concepts. The photos associated with each visual concept can then be analyzed to explore related travel experiences related to specific locations or traveler groups.

4   Research Progress

We demonstrate the effectiveness of the proposed method through a case study focused on South Korea as a tourism destination. We collected a large-scale dataset of travel photos from Flickr, a widely used

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[3] https://openai.com/index/clip/

photo-sharing platform in tourism research for analyzing travel experiences [12]. The dataset comprises 67,762 photos uploaded by 2,936 users, spanning the period from 2013 to 2024. To mitigate potential bias from users with a large number of photos, we capped the number of photos per user at 100.

Fig 2: Popular Travel Concepts in South Korea.

The visual concept modeling technique was then applied to the entire photo dataset, resulting in the identification of 216 distinct visual concepts. Fig. 2 illustrates examples of the most popular visual concepts identified. The most prevalent concept (concept 56) pertains to Korean foods, encompassing 5,459 photos, while the second most popular concept (concept 150) features traditional buildings, with 2,351 photos. Although concepts 56 and 199 may appear similar when described in words, as both are related to food or seafood, they represent distinct visual concepts. Concept 56 depicts food being served in restaurants, whereas concept 199 shows food being sold in markets. These visual distinctions reflect different travel experiences.

5   Conclusions and Future Works

In this working paper, we have demonstrated the advantages of visual concept modeling for discovering diverse travel experiences based directly on the visual content of travel photos. We plan to conduct further analysis of travel concepts across different locations to identify both common and unique travel experiences available in various regions of South Korea. Additionally, we will examine the differences in travel experience preferences among different traveler groups by analyzing

the travel concepts in relation to photos taken by users from each group.

The findings are expected to provide travel and tourism marketers, particularly those in South Korea, with a comprehensive overview of the various travel experiences available in the country, as well as insights into travelers' preferences. This will assist in developing targeted marketing strategies based on their interests. The introduced method is versatile and can be applied to travel photo datasets from any platform, offering broad applicability for various tourism-related applications.

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The Impact of Reviewer Expertise on Ratings: Evidence from TripAdvisor

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Abstract. This study investigates the relationship between reviewer expertise and ratings of public and private tourist points of interest on TripAdvisor. We analyse over 440,000 reviews across various locations in Europe and the Americas, categorizing the sites as either public or private based on their dependence on visitor revenue. Our findings confirm that experienced reviewers tend to provide lower ratings, but this effect varies significantly between public and private sites. Non-commercial sites show minimal variability in ratings regardless of reviewer experience, while commercial sites exhibit a clearer downward trend in ratings as expertise increases. These results suggest that businesses with a commercial interest may employ strategies to influence their ratings, challenging the assumption that inexperienced reviewers are more lenient. This methodology can be extended to other platforms, such as Google Maps, to identify review manipulation tactics more effectively.

1 Introduction

Online reviews have a significant impact on consumer decision-making, especially in the tourism industry (1). Studies have shown that online reviews can strongly influence purchasing decisions (2), and researchers have used hotel and tourist site reviews as a source of information, publishing hundreds of articles, with TripAdvisor being the most popular source of online reviews for tourism research (3,4). Compared to other review platforms that only focus on hotels, TripAdvisor's broader scope offers a more comprehensive dataset with reviews of private businesses, restaurants, and tourist attractions. In 2022 alone, more than 73 million reviews and opinions were submitted to the platform by 23 million members according to the platform's latest report

(5). The variables featured in TripAdvisor reviews, such as ratings from one to five, review content, geographic and demographic characteristics of users and level of experience on the platform, allow researchers to analyse characteristics that are highly useful for academic studies. The rating and the reviewer's level of experience are key factors influencing potential consumers (6–9). Research shows that experienced or credible reviewers tend to have a stronger impact (10), making it essential to explore whether their ratings differ from those of less experienced users. According to some articles dealing with other review platforms, more experienced reviewers tend to give lower ratings compared to less experienced ones (11–13), but the marginal effect of the level of reviewing expertise decreases (12). Taking these two factors into account, when aiming to positively influence consumer behaviour and enhance the profits of a particular business, it is essential to emphasize that tourism companies often tend to engage more in soliciting reviews, whether through legitimate means or by utilizing misleading opinions. Several studies have explored this phenomenon, suggesting that some companies implement strategies to artificially boost their ratings (14). These practices can include anything from the companies themselves or marketing agencies generating fake reviews to encouraging satisfied customers to leave feedback, while often neglecting to request that dissatisfied customers do so (15). Others, mainly hotels, often choose to use TripAdvisor's Review Express, a completely legal system of automated emails that reminds all customers to leave a review on the platform. This technique increases the volume of reviews and seems to improve the overall rating (16). According to Nam et al. (17), dissatisfaction acts as a stronger motivator for writing reviews (in this case, negative ones) than satisfaction, further highlighting the potential impact of these strategies.

In this working paper, we aim to investigate these two variables: the rating and the experience level of reviewers on the TripAdvisor platform regarding tourist points of interest (public and private interest) reviews. The goal of this research is to explore the relationship between rating and the experience level of reviewers and how they can influence each other. The research question is: Are there differences between ratings in private and public tourist points of interest based on the reviewer's experience level?

2   Methodology and Results

In order to determine the reviewer's level of experience, we follow the site's Member Achievements classification based on the number of contributions on TripAdvisor (18):

— First-timer: 1 contribution
— Newbie: 2 contributions
— Beginner: 3 to 4 contributions
— Rookie: 5 to 9 contributions
— Rising Star: 10 to 19 contributions
— Ace: 20 to 49 contributions
— Pro: 50 to 99 contributions
— Superstar: 100+ contributions

The Octoparse data scraping application was used to extract data. This software allows downloading content with unlimited records. The analysis was conducted on 227 tourist points of interest across the American continent (including the USA, Canada, Mexico, Argentina, and Brazil) and six European countries (UK, Turkey, Denmark, France, Spain, and Hungary) in December 2023. Tourist points of interest were selected from TripAdvisor and were categorized based on whether they are publicly and privately managed TripAdvisor organizes these sites according to its own criteria (such as cathedrals, parks, museums, and private tourism businesses). From this classification, we created our own grouping: public interest points (landmarks, national parks, and historical churches, etc.), which do not primarily depend on tourist revenue for sustainability (even if they charge an entry fee), and private interest points, which rely on visitor income, such as tour companies, theme parks, zoos, stadiums, etc. In the first case, there does not seem to be a clear commercial interest, so marketing actions that incentivize or solicit reviews, whether legal or illegal practices, are not expected. In the second case, since these businesses rely on visitor revenue, improvements in ratings are of greater importance, making actions to enhance these ratings more likely. A total of 444,273 reviews written in English have been analysed.

Table 1. Reviews Descriptive Statistics

Reviewer experience	Private				Public			
	N	Mean	Std. Deviation	Std. Error	N	Mean	Std. Deviation	Std. Error
First-timer	46,406	4.89	.545	.003	1,665	4.46	1.106	.027
Newbie	22,229	4.87	.569	.004	1,779	4.54	.962	.023
Beginner	24,814	4.84	.610	.004	4,280	4.57	.865	.013
Rookie	30,597	4.80	.638	.004	10,661	4.59	.805	.008
Rising-Star	28,923	4.75	.686	.004	17,491	4.57	.787	.006
Ace	37,178	4.71	.703	.004	36,333	4.56	.769	.004
Pro	24,620	4.67	.727	.005	33,780	4.55	.745	.004
Superstar	39,513	4.61	.735	.004	84,002	4.49	.736	.003
Total	**254,280**	**4.76**	**.662**	**.001**	**189,991**	**4.53**	**.763**	**.002**

Table 1 shows the descriptive statistics analysed, and in order to determine whether there are significant differences between the ratings of points of interest according to whether they are publicly or privately managed based on the type of TripAdvisor reviewer, we performed a one-way ANOVA test. Levene's test (p < 0.001) indicates that the assumption of homogeneity of variances was not met. Given the lack of variance homogeneity, post-hoc analysis was performed using the ANOVA Games-Howell test to examine differences between ratings across the eight reviewer types. The ANOVA results show significant differences in ratings for private points of interest ($F_{(7, 254,272)}$ = 815.173, p < 0.001) and public points of interest ($F_{(7, 189,983)}$ = 59.612, p < 0.001). For private points of interest, significant differences were found between all reviewer groups (p < 0.005). However, for public points of interest, the differences between the least and most experienced reviewers were not significant. For example, the difference between "First-timers" (1 contribution) and "Superstars" (100+ contributions) was not significant (p = 0.976), and similarly, no significant difference was found between "Newbies" (2 contributions) and "Pros" (50 to 99 contributions), with a p-value of 1. The results of this test confirm that all reviewer categories show significant differences among ratings, specifically of private points of interest. However, the difference between the ratings of public points of interest is not significant between less and more experienced reviewers on the platform, indicating that their ratings are very similar.

3   Conclusions and future research

Our findings confirm that, when analysing TripAdvisor reviews without distinguishing between public and private points of interest, more experienced users tend to give lower ratings overall, as suggested in previous studies (11–13). However, when we differentiate between sites with and without commercial interests, the situation changes significantly. We observe that points of interest without economic interest show little variability in ratings based on reviewer experience. These differences could be linked to the actions commonly employed by commercially-driven places. As various studies have suggested, some businesses engage in practices to solicit reviews, sometimes even using artificial methods to boost their ratings. This calls into question the assumption that less experienced users tend to give more positive reviews. Instead, we propose that users who are encouraged or incentivized to leave a review are more likely to provide favourable feedback. In fact, we observe that first-time reviewers, particularly for non-commercial sites, tend to give ratings that are either lower or similar to those of more experienced reviewers. This methodology could be extended to platforms with greater capacity to capture reviews, such as Google Maps, and could also serve as an indicator of businesses that employ specific strategies to boost positive reviews.

One key limitation of this working paper is the absence of a fully developed theoretical framework to underpin the research findings. While we have discussed related studies and contextualized our results within existing literature, a robust theoretical model—such as signalling theory (19) or other frameworks relevant to user-generated content—has not yet been explicitly incorporated. This is due to the nature of this work as a preliminary exploration of the topic. Additionally, the scope of this study was constrained by its adaptation into a working paper, restricting the number of reviews, points of interest, and geographic areas analysed.

For future research, we propose developing a comprehensive theoretical foundation to provide deeper insights and connections between the observed patterns in reviewer behaviour and broader theoretical constructs. Expanding the sample size, incorporating additional points of interest, and comparing geographic regions such as the Americas and Europe will allow for a more nuanced understanding of user-generated content (UGC) in the digital era. Furthermore, analysing additional variables and extending the methodology to platforms like Google Maps could yield even more valuable insights. These enhancements will be a central focus as we expand this working paper into a full research article.

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Smart Leisure Enabled Active Ageing Tourism Experiences

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Abstract. The number of ageing populations overlaps the productive ages who economically fund public services. It caused a significant effect on public health and economic prosperity and more spending on welfare, health, and social care as well as less tax revenue. This phenomenon has caused a serious issue in England and globally. To maintain the actively aged groups, the facilities provided by stakeholders are important for supporting the health and well-being of ageing population. The attributes of age-friendly facilities in the industry have not been explored thoroughly. Therefore, this study aimed to investigate the age-friendly facilities with the best practices that foster a convenient tourism environment. By using a different range of studies in the qualitative method, this research demonstrates the attributes' level of age-friendly facilities that vary. Results indicated that the available facilities and activities are sufficient to facilitate active ageing for their leisure experience. The studies also discovered best practices resources of preparing age-friendly environment.

Keywords: Smart Leisure, Active aging, Tourism, Experience.

1   Introduction

Stakeholders in the Hospitality and Tourism Industry can create an age-friendly ecosystem for active ageing (AA). The demand for senior tourists to engage in vacations with longer trips and personalised itineraries [2,3] opens the opportunity for the stakeholders to include actively aged people as part of the market segment. As a result, stakeholders that provide attractions, accessibility, amenities, activities and ancillary services [4], create a co-creation through the concept of smart leisure.

However, the conceptual model that explores how stakeholders can contribute to enhancing the tourism experience [5] needs further exploration, especially of how the resources can enhance the experience. Even though it is supported by a well-designed tourism service environment [6] how stakeholders in the H&T industry can enable the actively aged experience remains to be investigated.

This research aimed to explore the resources of hospitality and tourism industry to enhance leisure experiences for the elderly. How smart leisure including the facilities enabled the enhancement of the customer's experience. Therefore, four objectives guide this research: stakeholder resources identification, best practices of smart leisure, challenges and strategies for H&T stakeholders in supporting AA environments.

The research contributes to a clear link of how smart leisure enables AA tourism experience enhancement. As part of theoretical contributions, this research explored what resources are available in smart leisure ecosystem. How the ecosystem can enable the enhancement. The emphasis on the need for coordinated efforts among H&T stakeholders, including practitioners, policymakers, and community groups to create inclusive and accessible tourism experiences for elderly is also included in the result. Moreover, the study provided strategies for promoting AA, such as investing in staff training to improve services for the elderly and enhancing infrastructure and transportation systems for senior tourists.

2   Literature Review

Smartness is defined as an ecosystem that interconnects and serves many of the stakeholders. A study by Boes et al. (2016) investigates how technology as a hard smartness is used as a tool to fulfil the needs of soft smartness (innovation, social capital, human capital and leadership). Smartness relies on the availability of infostructures such as big data and sustainability [7]. For instance, service delivery is supported by information and communication technology (ICT) and offers real-time, personalised information for older adults' tourism experience [8]. Therefore, smart leisure combines the resources of stakeholders of H&T which includes innovation, social and human capital with the interconnection with technology [9].

Figure 1 shows how smart leisure creates an age-friendly environment through the collaboration of industry stakeholders and 4 pillars of active ageing; health, lifelong learning, participation, and security towards social connectedness. Co-creation value and social connectedness lead to a positive result that enhances the actively aged people experience.

The potential economic benefits of developing age-friendly tourism destinations are substantial and should be highlighted [5]. The current approach to age-friendly tour-ism facilities is often limited with accessibility being primarily interpreted as wheelchair access. A comprehensive understanding of accessibility should include provisions for varying physical and cognitive impairment levels, ensuring that tour-ism experiences are inclusive and enriching for all. The accessibility requirements for actively aged (AA) people vary for every individual [10].

3   Methodology

The research follows an interpretive paradigm to understand the subjective experiences of actively aged individuals within the H&T sector. The qualitative approach involved interviews [11] with 3 key stakeholders: hotel managers, and community volunteers. Direct observations of facilities and activities available for older people were conducted in 4 areas: Bournemouth, Christchurch, Poole and New Forest, in the UK. The study was conducted through netnograhy, observation and interview. Netnography was done through active ageing Facebook communities. Observations and interviews were done directly at the hotels such as Holiday Inn Bournemouth, Mariott High Cliff, Marsham Court, and Hilton. Restaurants; Harry Ramsden, Key West Bournemouth Pier. Transportation; More Bus. Attractions; Oceanarium Bournemouth, Russel-Cotes Museum, Highcliff Castle and community centres; Jolly Good company, Grounded Community. 31 people were interviewed including managers, staff, and volunteers. Most of the participants have exposure to people who are 50 years and above. Analysis was done by using thematic analysis which used code and interpreted qualitative data, ensuring the research findings were aligned with the study's objectives [11,12].
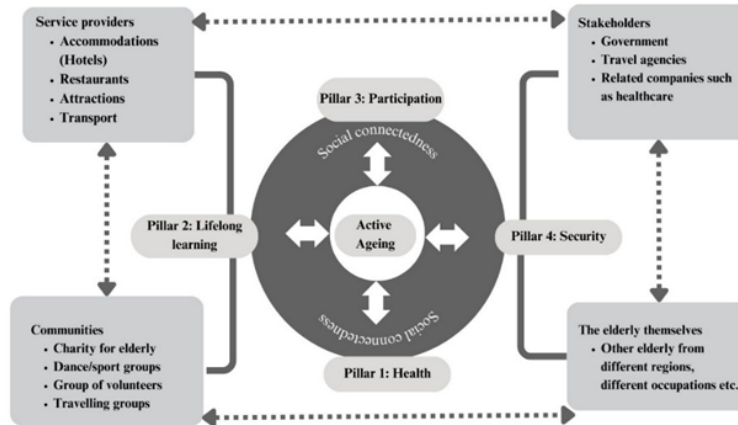
Fig. 1. The elements of smart leisure for enabling actively aged people experience.

4 Findings and Discussion

To understand how age-friendly facilities in the H&T industry can cater for the different levels of AA needs, the facilities of the stakeholders are divided into 7 sections: public areas outdoor and indoor, safety and security information availability, bedrooms, additional facilities, service and restaurant menu. The findings reveal that while several facilities are available to support AA, there is significant variance in their quality and accessibility.

Transport systems show consistency in providing accessible options, such as low-floor buses and clear signage. The community offers activities such as gardening and physical exercise classes, promoting both physical and mental well-being. However, challenges such as limited funding and insufficient facilities prevent many communities from fully meeting the needs of their elderly members. Challenges were found at micro, meso, and macro levels.

Stakeholders	Facilities	Activities	Remarks
Hotels, restaurants, attractions, community centre	Parking for people with disabilities close to the building	Swimming, Bowley, dance class, yoga class, birthday party, wedding anniversary, etc	Public areas (Outdoor)
	Easily recognisable entrance		
	Automatic doors at the entrance		
	Ramps to the building		
	Lower riser and wider tread stairs		
	Tactile guide paths for blind people (Optional)		
	Well-lit room		Public areas (Indoor) including lobby and restaurant
	Big signage for reception/concierge		
	Availability of padded with armrest chairs		
	Welcome drinks		
	Toilet on the ground floor		
	Accessible toilet on the ground floor		
	Available lift		
	Available accessible lift		
	Brail elevator		
	Lower riser and wider tread stairs with handrails		
	Availability of an "induction loop" for the hearing impaired using a hearing aid (e.g. at the reception desk, in public areas)		
	No Slip Surface		
	Easily recognisable emergency exits		Safety and security information
	Plan of evacuation for disabled people (including call point)		
	Availability of alternative fire alarm signal (e.g. vibration pad or flashing light for deaf persons)		
Hotels	Big signages		Bedrooms
	Convenient room access		
	Quiet environment		
	Soundproofing		
	Comfortable bedding		
	Walking shower		

Stakeholders	Facilities	Activities	Remarks
	No slip surfaces		
	The plugs and the light switches are reachable.		
	24-hour room service		
	Ergonomic furniture		
	Shower seats		
	Adjustable bed		
	Availability of accessible rooms		
	There are accessible twin rooms.		
	Guide dogs are allowed.		
	Toilet facilities for guide dogs		
	Availability of "induction loop" for the hearing impaired using a hearing aid (e.g. for the TV)		
Restaurants	Big signages		Menu
	No steps		
	Readable menu (big fonts)		
	Menu with nutrition information		
	Allergen information availability		
	Senior menu		
Hotels	Gym		Additional facilities
	Swimming pool		
	Changing places		
	Sensory room		
	Activities for active ageing		
	Available function room for activities		
	24-hour room service		Services
Hotels, restaurants, attraction	Senior discount		
Transport	Walking distance to bus stop 5-10 minutes from population living		Road Network (Areas of observation) Bournemouth, Christchurch, Pool (BCP), New Forest
	Walking distance to bus stop 5-10 minutes from workplaces		

Stakeholders	Facilities	Activities	Remarks
	Share of bicycle lane		
	Sidewalk availability		
	Pedestrian traffic signals		
	Maximum speed signals		
	Information about bus stop and bus departure/arrival		
	Punctuality of bus services		
	Security inside buses		
	Security at the bus station		
	Accessible toilet at the station		
	Behaviour of the bus driver		Vehicles Public transport; bus/ train/ taxi
	Affordable tickets		
	Availability of seats		
	Comfortable chairs		
	Anti-slip floor		
	Ramp		
	Disabled/priority seating		
	Low floor buses		
	Charging Plug		
	Ventilation		
	Adequate space for luggage		
Community Centre		Any type of activities	

Table 8. Best practice attribute list for enabling active ageing tourism experience [13

5   Conclusion and Recommendations

This research has added theoretical contributions by developing the link between age-friendly facilities and accessibility for people with different requirements. Smart leisure, which incorporates technology and stakeholder collaboration, is essential for achieving this goal. After identifying the available facilities, the stakeholders' facilities were analysed using a guided best practice attribute list instrument (See Table 1).

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Linguistic Features and Topical Differences in Hotel and Restaurant Reviews

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Abstract. This study investigates the linguistic features and topical differences between hotel and restaurant reviews to assess the impact of combining them in text analysis. A corpus of 20,402 reviews from the top hotels and restaurants in Shimla, India, was analyzed using Natural Language Processing (NLP) techniques in R. The study found that hotels receive significantly more reviews, while restaurants use a wider vocabulary due to the diversity in describing dishes and experiences. A chi-squared test revealed moderate similarities in vocabulary between hotel and restaurant reviews, but distinct word usage patterns. Structural Topic Modeling (STM) demonstrated that mixing both datasets obscures key topics specific to restaurant reviews, such as food and ambience, while hotel-related topics dominate. The study recommends caution in merging multi-type tourist reviews to avoid biases and highlights the need for future research on inherent characteristics in different review types.

Keywords: Text Reviews, Sentiment Analysis, Topic Modelling, Consumer Behavior, Tourist Experience.

1 Background

Text analysis is an established method in tourism research (Bi et al., 2024; Li et al., 2019). Tourist reviews, in text format particularly, are utilised for understanding consumer behaviour for various purposes (Fitchett & Hoogendoorn, 2019; Mary & Pour, 2022; Taecharungroj & Mathayomchan, 2019). But, understanding the inherent nature of this data has never been a topic of interest. The tourist reviews can be of certain types like hotel, restaurant, activities, architectural, sightseeing, guide services, and local culture related. The question of understanding tourist experiences through tourist reviews at a destination can drive a researcher to mix all types of reviews to gain a comprehensive view of the destination. However, this paper argues that mixing all types of reviews can be misleading because it may lead to certain biases in the results like certain portion of data diminishing the effect of other datasets.

For example, it is apparent that a restaurant review is more likely to be concerned with dishes, food, taste, ambience, staff or services, while hotel reviews more likely to cover little broader facets of the tourist experience like hotel rooms, hotel's restaurant, ambience, location, and staff, so if both datasets are mixed together, it is likely that one data type will diminish the effect of the other and the results will be biased towards a certain portion of data. Hence, to study this potential anomaly, the current study aims to statistically test the differences between hotel and restaurant reviews. The outcome of understanding such differences will be helpful for future researchers to choose the right dataset for understanding tourist behaviour using text review data.

1.1 Objectives

- To statistically test difference between top word distributions in Hotel and Restaurant Reviews.
- To understand the effect of combining both datasets on topic modelling of tourist experiences through textual reviews.

2 Methodology

As a pilot project, the review data was collected from the TripAdvisor platform by following a criterion of top 10 hotels and top 10 restaurants in Shimla (a popular hill station of India) based on the number of reviews. The data was scraped using a web scraper on xlsx spreadsheets. The total number of reviews collected were 4,838 in restaurants and 15,564 in hotels, so a total corpus of 20,402 reviews, as of 30 July 2024. For data pre-processing, datasets were imported into R. Standard Natural Language Processing (NLP) procedures for text cleaning were applied using Quanteda framework (Benoit et al., 2018).

   For text modelling, initially traditional Latent Dirichlet Allocation (LDA) approach was experimented separately on both (hotel and restaurant) datasets, showing greater number and depth in topics. However, to understand the effect of mixing both datasets (hotel and restaurants) on topics/themes, the Structural Topic Modelling (STM) approach was found more suitable. STM was chosen over LDA due to its advantage of incorporating meta-data covariates (restaurant or hotel) into the model. Hence, the data was finally modelled using STM framework in R (Roberts et al., 2019).
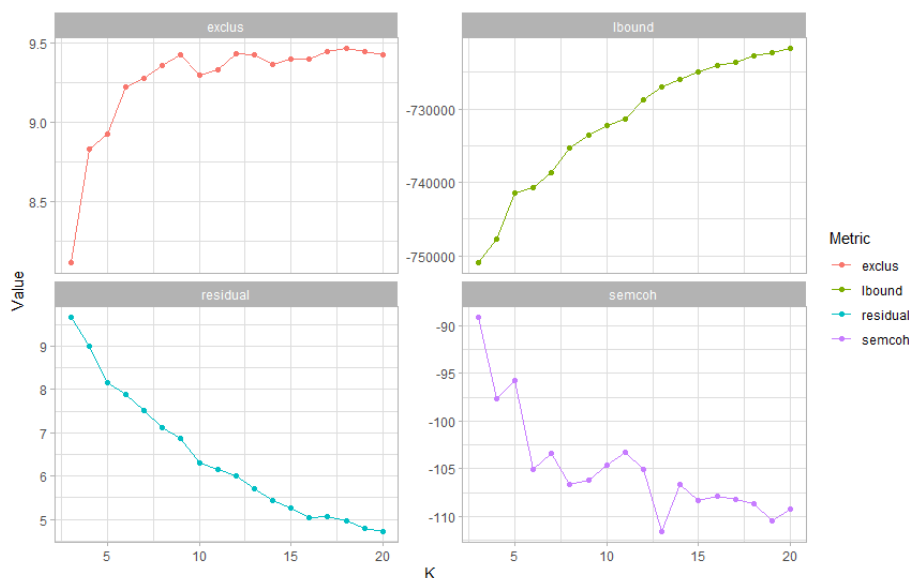
Fig. 12. Metrics used to find ideal number of K or Topics.

Various matrices such as exclusivity, lower bound, residual, and semantic coherence was used to identify ideal number of topics by calculating scores for 3 to 30 topics (Figure 1). Ideal number of topics was chosen by keeping residual low and remaining (semcoh, exclus, lbound) metrices high (Weston et al., 2023). Consequently, an 18 K topic model was selected and the topics were labelled by qualitatively exploring the documents linked to topics. Additionally, to understand the effect of metadata on topics, correlation coefficients were calculated and visualised. Moreover, help and suggestions were taken from Large Language Models (LLMs) for various tasks.

3 Results

Tokenization of a 20, 402 review corpus resulted in 5, 071 unique features (or vocabulary) with a sparsity level of 99.42% in the overall document feature matrix. Figure 2 show that the distribution of words was right-skewed in both datasets, i.e., many words with low frequencies - and fewer words with high frequencies. The plot highlights the fact that restaurant corpus uses many words that are used less frequently. This is likely due to wider range of words used to describe dishes and ingredients, while the hotel seems to be using more standard vocabulary.
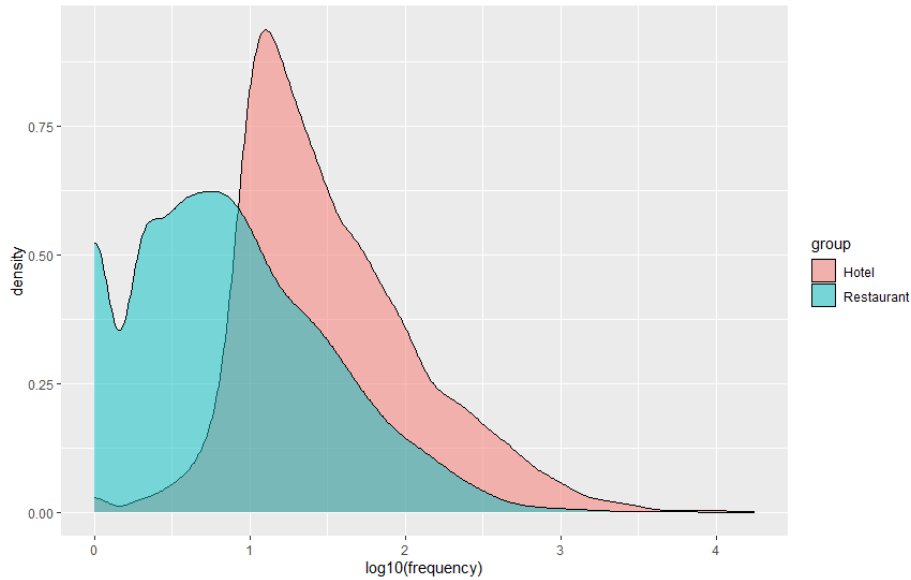
Fig. 2. Distribution of word frequencies for Hotel and Restaurant Reviews using a density plot.

3.1 Objective 1 Results

The Pearson's Chi-squared test for testing difference between word distributions in hotel and restaurant reviews have shown substantial difference with X-squared value of 144787, along with 5071 degree of freedom (DF) and an extremely small p-value $<$2.2e-16 indicating strong evidence against the null hypothesis. For better understanding of these results, effect size was calculated using Cramer's V which has shown a strength of association at 0.47 level. This means there was moderate association between the word distributions of hotel and restaurant datasets. Implying that the restaurants and hotels reviews use moderately similar word yet they are widely distinct. Table 01 highlights the top 5 words with largest differences.

Table 9. Top 5 words with largest differences.

Word	Hotel	Restaurant	Difference
hotel	17668	275	17393
staff	11663	924	10739
room	8895	53	8842
stay	8401	89	8312

| rooms | 5826 | 8 | 5818 |

3.2 Objective 2 Results

The results of the estimated effect calculated using a regression method, i.e., the effect of restaurant and hotel datasets on topic generation, were visualised in Figure 3. The largest difference was found in topic 5 with a 0.172560 positive coefficient score, other topics such as topic 16 (0.133334), topic 13 (0.132564), topic 9 (0.042308), and topic 2 (0.005066), were also prevalent in restaurant reviews. In the hotel's corpus, topic 11 with a negative coefficient score of -0.085131 was most significant, followed by topic 1 (-0.065995), topic 6 (-0.056616), topic 3 (-0.054478) and others. This implies that Café Items, Restaurant Location and Food, and Dinner Items were more associated with restaurant corpus, while Hospitality Experience, Hotel Location, Spacious and Peacefulness, and Praising Staff, were the predominant topics of hotel corpus.
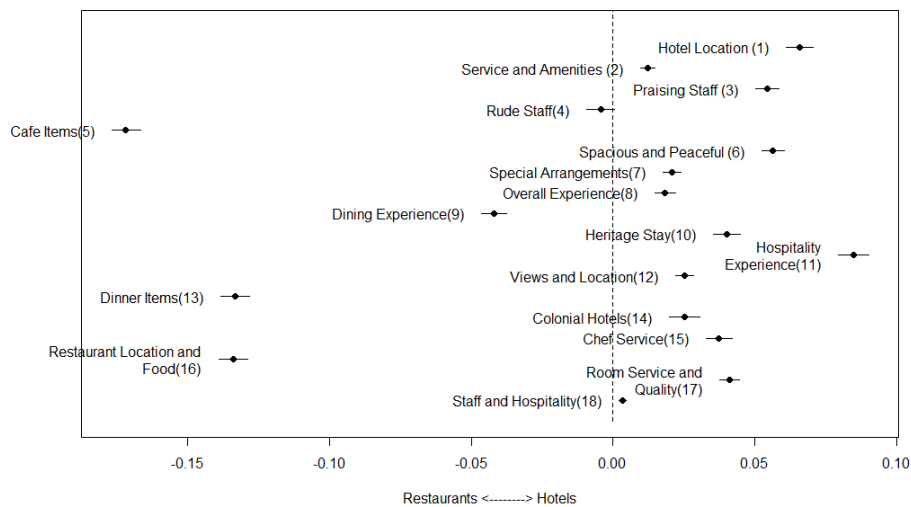

Fig. 3. Prevalence of topics in datasets (restaurant and hotels).

4 Conclusion

From the current study on differences between hotel and restaurant reviews, the following points can be concluded: (1) It was observed that

hotels receive higher number of reviews than restaurants. So mixing both is likely to bias the results towards the hotel corpus; (2) restaurants uses wider vocabulary than hotels, and as per the density plot, restaurant have large number of words that are used less frequently in comparison to hotels, due to wide range of words used to describe dishes, ingredients, and experiences in restaurants; (3) as per the chi-squared test between the distributions of words in hotel and restaurant reviews, the results conclude that both use moderately similar vocabulary (due to hospitality nature of both) yet they differ on wider word choices; (4) in topic modelling, it was found that mixing of both restaurant and hotel reviews diminishes the effect of inherent topics present in restaurant data (or the dataset with lower number of reviews). For example, our STM model was not able to detect topics such as dishes, food, taste, ambience, staff, and services, in restaurant review, while they were detected when applying topic modelling on separate datasets.

5   Implications

The current author suggests future researchers to practice utmost cautions before mixing multi-type tourist reviews, because the size and vocabulary of the datasets is most likely to create biases. Additionally, this study proposes a new research area to study the inherent characteristics in various tourist review types. Outcomes of such an exploration will be helpful in the future to understand/construct tourist behaviour insights from the reviews.

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Section 6: Smart Destination Policy

Smartening tourism governance in European cities: a discourse and sentiment analysis based on BERT

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Abstract. The adoption of smart city agendas and policies in urban tourism destinations is perceived as a new stage in tourism planning toward cleaner, more efficient, and more inclusive destinations. In this context, Europe boasts many of the world's top urban destinations that offer a unique and urgent context for the deployment of smart destination solutions. However, the operational understanding and the challenges of integrating tourism as a critical element of smart city development and the assessment of the real impact of smart solutions at the local level remain underrepresented topics in the academic literature. The main goal of this paper is to address this gap by analyzing the positions, discourses, and levels of representation of a sample of stakeholders involved in — or who should be involved in — tourism planning and 'smart city' ecosystems across selected European urban destinations. The analysis focuses on various tourism-related challenges, such as the future of tourism, its social impacts, and the transition to sustainability, with particular attention to how 'smart' urban development can play a pivotal role in addressing these issues. This analysis uses discourse and sentiment analysis through an innovative methodology based on BERT (Bidirectional Encoder Representations from Transformers), which allows tracking and orders a significant number of stakeholders' opinions on a real-time basis and identifies opportunities for collaboration in alignments of opinions and activities as a shared understanding measure. Ultimately, we expect to shed light on the key challenges and opportunities for governance in cities where 'smart' is expected to represent a turning point for coping with the transformations triggered by tourism.

Keywords: tourism planning, tourism ecosystem, governance, smart city agenda, discourse analysis

6 Introduction and Analytical Framework

Tourism plays a vital role in Europe, significantly contributing to economic growth, employment, and cultural exchanges (Bramwell & Lane, 2011 [1]). However, the complexities of this sector demand scrutiny, especially as transformative changes call into question the effectiveness and discourses of current governance mechanisms. This study examines seven case study cities—Amsterdam, Barcelona, Lisbon, Venice,

Ljubljana, Jerusalem, and Turin—each facing challenges related to mobility and sustainability. Notably, Turin, while still an emerging tourist destination, has been included for its relevance as a hub for student and other mobility types, offering a unique point of comparison.

The rise of smart specialisation has been a major milestone in the progress of urban and regional policy in Europe (Foray et al., 2011[2]; McCann et al., 2015[3]). It relies on more than twenty-five years of extensive experience in multi-level governance in a variety of territorial settings across the continent. This has coincided with the development of ICT-focused policies in tourism, urban development, and governance. Tourism strategies tied to the smart city (SC) paradigm emphasize boosting innovation and competitiveness through cross-sector collaboration (Baggio, 2020 [4]).

While SC development broadly aims to enhance urban efficiency and sustainability (Gretzel, 2018 [5]), tourism is rarely acknowledged as a critical component in SC planning (Gretzel & Koo, 2021 [6]). Moreover, the limited availability of case studies on specific SC initiatives (Kitchin, 2015 [7]) and the tangible impacts of smart solutions at the local level (Buonincontri & Micera, 2016 [8]; da Costa Liberato et al., 2018 [9]; Femenía-Serra & Ivars-Baidal, 2018 [10]) reveal significant research gaps. This mirrors broader omissions regarding the social consequences of tourism development in developed economies (Romao & Neuts, 2017 [11]). Governance in tourism often excludes diverse stakeholders, focusing predominantly on industry leaders (Moscardo, 2011 [12]; Ivars-Baidal & Vera-Rebollo, 2019 [13]). Consequently, social agents with vested interests in tourist spaces and urban economies are frequently excluded from critical decision-making processes (Bramwell & Lane, 2011 [1]).

Regarding the case study cities, while Amsterdam, Lisbon, and Turin can be identified as cities with an established SC strategy, none of them have directly linked their tourism governance to a specific smart strategy based on the concept of smart destinations. Only Barcelona since the end of 2023 counts with a common strategy of Smart Tourist Destination (Ajuntament de Barcelona, 2023 [14]). Our research strategy begins by exploring transversal and comparable processes across the case study cities, focusing on the analysis of diverse perspectives, mindsets, and the polarization of discursive practices surrounding the integration of different forms of mobilities and social effects into the SC discourse, with particular attention to the local impact of smart solutions. In this

context, integrating smart tourism with a regenerative tourism approach becomes essential within contemporary socio-economic and tourism frameworks. Unlike the sustainable development model, regenerative tourism views tourism activities as interventions that improve the ability of locations, communities, and visitors to thrive together within interconnected social-ecological systems (Bellato et al., 2023 [15]).

This study addresses a gap in existing research by analyzing the roles, discourses, and levels of representation of various stakeholders—such as public administration officials, industry representatives, innovation agents, social and grassroots movements, and ICT sector actors. This diverse group is integral to tourism planning and smart city ecosystems, enabling the detection of a shift in discourse toward more regenerative tourism planning. The data was collected during a period of significant uncertainty, marked by the emergence of discourses shaped by the ongoing COVID-19 crisis. This crisis unfolded alongside a range of other challenges, including socio-political issues and shifts in production and consumer demand, contributing to a broader polycrisis (Ioannides & Gyimothy, 2020 [16]).

This study offers valuable insights into shared processes observed across various case studies, highlighting common macro-themes in tourism. By examining multiple cities, it seeks to deepen understanding of the interplay between smart city (SC) approaches, regenerative tourism policies, and social actions tied to tourism interactions, ultimately exploring the relationship between socio-political and socio-technical regimes. Framed within a temporally disruptive transition marked by significant upheaval—from conventional scientific paradigms to a new collective consciousness (Dredge, 2022 [17]) —the research addresses how different stakeholder groups in urban tourism governance perceive and engage with SC initiatives and examines the implications for advancing regenerative tourism strategies.

7   Sources and Methods

This study utilized a combination of literature review and empirical research, incorporating methods such as content analysis, agent mapping, and network analysis, previously applied within the SMARTDEST project (Horizon 2020). The research unfolded in three phases: (i) Data Collection, where information on tourism governance and the smart city (SC) approach was gathered separately through content analysis of

official websites, policy documents, and planning frameworks. This phase identified key themes and gaps in governance strategies, shaping the development of a comprehensive interview guide; (ii) Agent Mapping and Network Analysis, which used agent mapping and social network analysis to visualize the formal structures of tourism and smart governance in each case study city. Utilizing Gephi software, these analyses mapped the networks of agents within the planning ecosystem, contextualizing stakeholder perspectives and informing the subsequent triangulation in the analysis; and (iii) Analytical Comparison, focusing on comparative analysis across case studies to identify recurring issues across cities or stakeholder categories and to represent stakeholder discourses within their specific urban contexts.

To enhance the analysis, an innovative methodology was developed leveraging BERT (Bidirectional Encoder Representations from Transformers), an advanced natural language processing (NLP) model by Google. BERT's bidirectional context understanding excels in topic detection and sentiment analysis, enabling a deeper examination of stakeholder collaboration and emergent themes.

Additionally, the study employed a semi-structured interview approach to explore unforeseen issues and perspectives. The interview protocol covered topics such as stakeholders' roles in urban tourism governance, their perceptions of SC initiatives, and their views on policy frameworks and planning tools. Stakeholders were selected through purposive sampling to ensure diverse representation, including public administration, industry, innovation agents, and social movements.

In the preliminary results from Barcelona, a sample of 26 stakeholders (n=26) was analyzed. These semi-structured interviews, featuring open-ended questions, allowed participants to elaborate on governance challenges and opportunities specific to their city. Invitations for interviews were sent via email, with interviews conducted virtually or in person depending on availability.

8   Preliminary results

The analysis of the interviews is intended to be applied to the entire dataset. However, this process is still ongoing. At present, the preliminary results of the project are based on an analysis conducted on a database of interviews with 26 stakeholders operating in Barcelona. In subse-

quent phases, this methodology will be applied to all case studies, encompassing the full dataset. Each interview was coded with a unique ID to identify, the role of the interviewee's organization in the tourism industry(user), the geographical scope of the organization's competence (user.level), the interviewee's gender (user.gender), and the interview text in English (Interview).

The analysis comprised three distinct phases. In the first phase, BERT detected the most relevant topics raised by stakeholders during their interviews. The topic detection process was performed on the entire interview text, disregarding the interview ID.

In the second phase, BERT assessed the extent to which each stakeholder associated with the topics i.e., the actor states a statement or takes a position on that topic. The association index ranged from -1 to 1, indicating the topic's relevance for the stakeholder and their sentiment towards it. For example, a value of -1 signified that the topic was relevant to the stakeholder, but they expressed a negative sentiment towards it (see Figure 1).
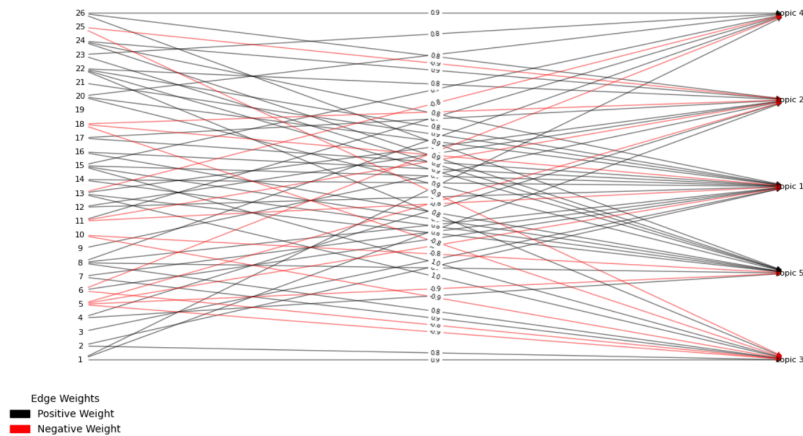
Figure 1. Topic Relevance by Stakeholder

Finally, in the third phase, we evaluated the degree of shared understanding among stakeholders in their interviews as an indicator of potential collaboration. This analysis yielded a network of stakeholders, where the strength and sign of relationships indicated the extent of collaboration potential. A strong and positive relationship implied a shared understanding of the topics discussed, while a negative and strong relationship indicated similar topic interests but opposing positions among stakeholders

9   Conclusions and Future Research Directions

The added value of this research lies in connecting key concepts such as stakeholder collaboration, the integration of regenerative tourism within smart city frameworks, and the socio-political dynamics of urban tourism governance. A particular focus is placed on stakeholder positioning (conformity vs. disconformity) regarding key tourism-related topics emerging within the destination ecosystem of each case study. This approach allows for an assessment of urban tourism governance, the level of stakeholder involvement, and the evolution of the stakeholder map over time.

To achieve these objectives, the research will proceed in several steps: (i) Scaling up the research process: Expanding the analysis to include all case studies enables a comprehensive and comparative evaluation. This broader scope will deepen the understanding of stakeholder positioning across diverse destinations, revealing both commonalities and differences in urban tourism governance. (ii) Enhancing the algorithm: Continuous refinement of the algorithm used in the research is essential to improve its accuracy and reliability. Ongoing efforts to optimize the algorithm will ensure the generation of precise and robust results, enhancing the overall quality and impact of the study. (iii) Synthesizing insights: By integrating these improvements, the research aims to provide a holistic assessment of stakeholder positioning and the evolving dynamics within destination ecosystems across multiple case studies. These efforts will contribute to a deeper understanding of urban tourism governance and offer valuable insights for policymakers, destination managers, and other stakeholders involved in the tourism industry, supporting the development of more effective and inclusive governance frameworks.

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Short term rentals in coastal areas: management issues and challenges from a smart destination perspective

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Abstract. Unlike their impact on large cities, the effects of the recent boom in STRs have been little studied in coastal destinations. This working paper explores the difficulty of measuring this type of supply and its various implications for both destination management and the evolution of the tourism development model. Through a case study that applies a smart destination strategy, different management challenges and future lines of research are identified.

Keywords: short-term rentals; coastal destinations; smart tourism destinations

1   Introduction

The impact of short-term rentals (STRs) is being widely studied in urban destinations. However, few studies have focused on the implications of this type of accommodation in coastal destinations. Short term rentals are a traditional form of accommodation in sun and beach destinations, even, in many cases, quantitatively superior to the hotel supply. This type of accommodation is clearly connected with the urban growth of Mediterranean destinations, with the different forms of mobility that converge in these areas (second homes, climate migrants, etc.), which temporarily free up housing for the tourist rental market, and with the purchase of housing as an investment asset.
In the Spanish mainland Mediterranean, the tourist rental supply has been regulated as tourist apartments, either in blocks or in individual units, although the regulated supply has traditionally coexisted with a considerable volume of illegal supply, outside administrative control. This structural characteristic of coastal destinations has been altered with the rise of online marketing and platform economies. There has

been a growth in the STRs supply with implications in terms of tourism, socioeconomic and territorial aspects that cause both opportunities and problems of different kind.

2   Objectives and methodology

This paper has three interconnected objectives. First, to explore the possibilities of measuring and quantifying the growth of short-term rental; second, to identify the implications of this growth in coastal destinations; and third, to assess the advantages and disadvantages of addressing this issue from the point of view of smart destinations (SD).
The work has a clearly exploratory approach and combines the analysis of information sources to measure the evolution of STR with a case study, the municipality of Calpe, a destination with a significant degree of maturity from the point of view of the SD model. In this destination, preliminary analyses of different data sources are carried out and different plans and technical reports are studied to identify the implications of the growth of this type of supply and the management challenges and new research needs they raise.
The case study, Calpe, is a well-established tourist destination in the Spanish Mediterranean coast according to Perles et al. (2017) [1]. From 1960 to 2007, Calpe transformed dramatically from a traditional agricultural and fishing village into a prominent tourist destination. The development model has strong inertia, suggesting that only land depletion or economic downturns could effectively slow growth.
However, Calpe's heavy reliance on "sun and beach" tourism poses risks, making it vulnerable to economic fluctuations. Recent economic and financial crises and COVID-19 have impacted local economic indicators like employment and income, suggesting that construction and property development may become less significant in the future and highlighting the weakness of tourism activity.
The resulting issues hinder Calpe's tourism competitiveness and sustainability. Recent efforts by local authorities to address imbalances have aimed to turn Calpe into a Smart Destination. To this end, Calpe is applying a Master Plan and implementing significant actions in the areas of technology and governance, leveraging funding from various European funds such as Next Generation.

3   Preliminary results

3.1   The difficult measurement of STRs at the local level

Calpe has more dwellings (26,156 according to the 2021 Housing Census) than registered persons (25,854 residents in 2023). This significant volume of dwellings has historically formed the basis of tourist accommodation in the form of second homes and tourist rentals, with high occupancy in the summer months. This structural feature of its tourist model is entrenched in the last three Housing Censuses (2001, 2011 and 2021) where the number of non-primary dwellings rises from 58.7% to 62.3%, an evolution that is accompanied by the explosive growth of tourist rentals in the period 2015-2020 (see Fig.1). Data derived from the regional administrative database (*Turisme Comunitat Valenciana*, TCV) show the evolution in the structure of bedplaces in the destination.
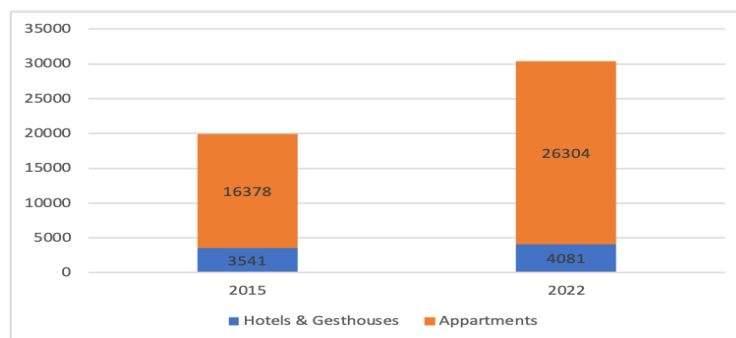
Fig. 13. Tourist accommodation bedplaces in Calpe (2015-2022)

This number of bedplaces, translated into dwellings, would mean going from 2,929 tourist apartments in 2015 to 5,267 in 2022 (a somewhat high average of 5 beds per apartment). In a period in which the pace of construction is slowing down compared to previous periods, this variation is not explained by the construction of new homes and is directly related to the emergence of rentals that are marketed on platforms over which the different administrations are trying to exercise greater control. However, the official data do not seem to reflect a reality whose measurement is really complex and which is trying to be approximated by means of new statistical operations.

Figure 2 shows the disparity in data between the administrative records (TCV) and the experimental survey conducted by the National Statistics Institute (INE) in February and August of each year, applying web scraping techniques to the three main STR platforms in Spain. Moreover, the gap widens progressively as the increasing limitations to the increase of STRs at local level and the new regional regulation favor the registration of new tourist accommodation units. Between January 2023 and May 2024, 1,000 new tourist dwellings were registered in Calpe, a dynamic that is also observed in other coastal municipalities of the Valencian Region.
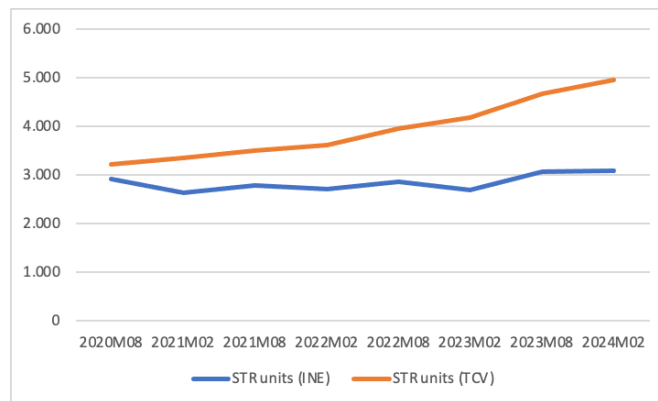
Fig. 2. Evolution of STRs units: TCV versus INE

Based on the 2021 Housing Census, the INE measures the intensity of electricity consumption per dwelling, which reflects that 18% of dwellings are empty and 40.6% have sporadic or low consumption, showing the contrast between the high consumption of land for dwellings and the seasonal use typical of many Mediterranean destinations.

On the other hand, compared to the generally static hotel offer, the STRs are a dynamic offer with a marked fluctuation that is corroborated by other sources such as AirDNA, by collecting blocked days, days when the owner does not offer the apartment, particularly relevant in a municipality with such a high percentage of second homes and small property owners. Another dimension of analysis lies in measuring the percentage of peer-to-peer accommodation and exploring the causes of an a priori marginal share of the destination's supply.

It is also important to know the territorial distribution of STRs, especially the percentage they represent of the total number of dwellings.

The INE's experimental statistics show these data broken down by census sections and corroborate a greater presence of STRs in dispersed residential areas with single-family homes (around 20%), followed by urban areas adjacent to beaches (over 10%), with apartment buildings as the most characteristic urban typology, and a lesser presence in the traditional urban area.

3.2   Causes and implications of the growth of STRs

Neither the causes nor the implications of STRs are the same as for urban destinations. The causes include the rise of digital platforms, but also the attractiveness of home buying for investment purposes (buy to let in many cases), particularly for foreigners in the municipality studied; new forms of mobility; the close relationship between construction and tourism, with urban plans that still maintain high growth potential; and the existence of a voluminous stock of vacant housing that could be integrated into the rental market (second homes).

Among the positive implications is the regularization of illegal supply, traditionally marketed through informal circuits without quality requirements and, in general, outside fiscal control, as well as the possibility of using the greater commercial visibility of the STRs to combat seasonality. The data analyzed show that Calpe is experiencing a gradual process of deseasonalization, but no cause-effect relationship can be established with the growth of the STRs.

Among the negative implications, its contribution to the increase in land and housing prices stands out, both for purchase and permanent rental, an aspect contrasted fundamentally in urban destinations in Spain, such as Madrid, Barcelona or San Sebastian, but also in coastal destinations in Andalusia (Rodríguez-Pérez de Arenaza et al., 2019) [2]. Although the measurement of this effect is very complex, local media attribute to STRs a clear responsibility in the difficulty of access to housing and the expulsion of the population to neighboring inland municipalities. In addition, differences are observed in the analysis of the price formation of tourist rental if it is an urban or a holiday destination (Moreno-Izquierdo et al., 2019) [3]. Preliminary analysis for this working paper suggests that there is cointegration between the number of tourist dwellings and the purchase and rental prices. They also point to the existence of a unidirectional Granger causality from the number of dwellings to prices.

The relationship with overcrowding is not so clear since this is a destination used to summer peaks of occupation where congestion of beaches and public spaces is common in the summer months. The perception of local society with respect to overcrowding has been analyzed in specific surveys and does not show a significant degree of concern, while a negative perception is not detected among the demand, since the levels of satisfaction with the destination measured through different indicators are high.

Although there is no data to support the effect of the growth of STRs on local quality of life, this process is a central element in the debate on the tourism development model of municipalities such as Calpe, questioned because coastal tourist destinations generally have a lower average income per inhabitant than the regional average, partly due to a statistical bias insofar as a high percentage of residents pay taxes outside the municipality and due to the greater presence of the informal economy. These income levels, together with the high cost of living, a growing tax burden on residents, the predominance of low-wage jobs (hotels and restaurants; maintenance of houses, swimming pools, gardens, etc.), greater social awareness of the imbalances of tourism and its vulnerability to episodes such as Covid-19, and the greater investment effort by public administrations to meet the needs of visitors, highlight the risks of excessive dependence on tourism. The role of the STRs in this tourism development model is insufficiently analyzed: How has the growth of STRs contributed to the increase in post-pandemic demand? Is the impact on house purchase and rental prices of this first analysis confirmed? To what extent does it encourage buy-to-let and urban growth? who benefits from this type of development? Will it negatively affect other types of commercial supply in terms of occupancy and price level? Some questions can be answered now, such as the null effect, for the moment, of VUTs on hotel occupancy and prices according to available data, but others imply the need for a forward-looking view.

3.3 The management of STRs from the smart destination perspective: progress and challenges

Among the advances detected, it is worth mentioning the greater availability of sources and disaggregation of data thanks to the improvement of the tourism information system that involves the evolution towards

the SD model (Ivars-Baidal et al., 2021) [4]. The creation of a tourism intelligence system with the application of Big Data techniques is included in the Calpe SD Master Plan (Calpe City Council, 2017) and has resulted in a quantitative and qualitative improvement of the information available thanks to data derived mainly from mobile phones and information obtained from social networks. These sources are complemented by traditional operations such as demand surveys and monitoring the occupancy of tourist accommodation establishments.

However, relevant challenges remain, such as the integration of tourism information with other municipal areas such as urban planning and environment or the construction of time series that allow more sophisticated analysis. In this sense, it is very interesting to integrate tourist occupancy data with energy and water consumption to better estimate the number of visitors throughout the year and evaluate the pressure on natural resources. The analysis of water consumption over the last 10 years shows, for example, a marginal growth in consumption despite the growth in demand thanks to improved efficiency in management and a reduction in seasonality to the extent that consumption in the summer months has gone from 36% to 33% of annual consumption.

On the other hand, destination management has not yet considered the use of specific technologies for the detection of illegal accommodation marketed online; data derived from smart metering in water management for the differentiated tax treatment of dwellings (although it is used, logically, to calculate payment for consumption and also for the detection and reporting of leaks); or the use of technological devices to ensure coexistence in mixed residential and tourist areas (access controls, sound meters, etc).

4   Conclusions

The disruptive growth of STRs in coastal destinations requires specific studies to help quantify and manage this phenomenon due to the diversity and importance of the implications shown in this exploratory case study. A better understanding of the interaction of STRs in these destinations is essential for their tourism, urban and even fiscal regulation, but also for the redefinition of coastal tourism models through renewed strategic planning that incorporates the use of technology and data both in the analytical dimension and in the solutions applied to specific problems.

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Smart Tourism for economic growth

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Abstract. Amidst the global geopolitical uncertainty, environmental risks, and economic volatility there is a need for a contemporary strategic and holistic approach to be adopted by tourism destinations. The proliferation of information and communication technologies (ICT) are providing promising solutions in this direction. Destinations adopt modern ICT and focus on building digital infrastructure, making smart destinations the new norm. The concept of smart tourism (ST) destinations emerged by integrating modern technologies and intelligence at the destination level. It provides infostructure, networking various stakeholders and re-engineering processes and data. That provide innovative services, products and procedures towards maximizing performance and optimize values for entire network of stakeholders. There is a lack of literature on economics and ST. The aim of this paper is to explore the potential economic impacts of ST. A comprehensive literature search is conducted and a critical review approach is used to synthesize and analyse the existing literature. The study contributes by extending the concept of ST by examining the economic view point of ST in providing economic benefits for destinations.

Keywords: Smart tourism destination, Economic Benefits, Information Communication Technology (ICT)

1   Introduction

The tourism industry is one of the fastest growing industries globally. Historically it contributes a tenth of global GDP and employment [38]. In 2023, tourism contributed an estimated $3.4 trillion, accounting for 3% of the global GDP and increased its workforce by 27.4 million with a total nearing to 330 million jobs worldwide [37, 39]. Even with this positive trajectory of the industry, the rise in current issues such as global geopolitical uncertainty, fiscal profligacy, price inflation, sticky wages, unemployment, environmental risks, addressing the legacies of economic crisis and anti-tourism sentiments etc. pose a need for a pragmatic and holistic approach to be adopted by the key decision makers [22].

The proliferation of ICTs such as Artificial Intelligence (AI), Blockchain Technologies, Extended Reality (XR), Robotics, Machine Learning, Metaverse, Cloud Computing, Generative AI e.g. Generative Pretrained Transformer (GPT), shape the economies for future [6]. They provide a diverse range of opportunities and challenges to tackle contemporary problems [31, 15, 26]. Across industries it is estimated that analytical and AI can annually contribute $11 trillion to $17 trillion to the economic value, whereas Generative AI is estimated to potentially deliver economic benefits of $2.6 trillion to $4.4 trillion [11]. Metaverse could provide market opportunities of $800 million [21]. Blockchain technologies supply chain market value is anticipated to increase from $1.47 billion to $75.38 billion by 2032 [35]. With ICTs having immense economic potential more destinations are focusing on "ICT readiness". Thus, building infrastructure to take advantage of these technologies, making smart destinations the new norm for the coming years [38].

The notion of ST was amplified with the development of Smart Cities [5], where development of the city is powered, supported and integrated by digital technologies to cope with propelling urbanization [18]. The concept of smart tourism (ST) destinations emerged by integrating modern technologies and intelligence at the destination [2, 8]. Since then, there has been a paradigm shift in the manner in which tourism is managed and conceptualized [20]. "Smart" is based on Theoretical foundations, Networking, Smart Ecosystems, Sustainability, Adoption of Technologies, Smart Systems and Processes, Planning and Policy, etc., [30, 16, 25, 32]. Destination Smartness therefore refers to the ICT enabled destination ecosystem that is using advance technology to enhance competitiveness of the entire network of stakeholders [6].

2   Research Aim and Objective

In spite of an increasing body of literature on ST destinations there is sanctity of literature on what are the economic benefits of ST. Therefore, the aim of this paper is to explore the potential economic benefits of ST and how these can contribute to its competitiveness. A comprehensive literature search was conducted using different bibliographic data bases. A wide range of academic studies such as research articles, books, reports, etc. (published from 2013-2024) were selected and in-

cluded in the work. The search terms included "smart tourism and economics", "smart tourism destinations", "smart tourism destination competitiveness", "smart tourism ecosystems". A critical review was conducted to assess, synthesise and analyse the existing literature. A conceptual framework was then developed based on the literature to show the role of smart tourism on the destination's economy.

3   Conceptual Framework

The literature illustrates that developing a ST destination requires authentic leader [34]. Leadership plays a critical role by initiating the necessary steps in making investments to bring smartness [4] These investments are made for creating and upgrading digital infrastructure [27]. Leadership is also critical for bringing different actors to coordinate efforts and resources. Generally, these are done by the local government authorities such as municipality or DMOs [23, 19]. The different stakeholders at destination are networked together using these digital platforms. This infostructure enables them to engage in co-creation of value [24]. Stakeholders can be divided into supply side including local planning authorities, DMOs, local businesses, tourism intermediaries, academia etc. and demand side including the tourism consumers, interest groups, local residents etc.

3.1   Destination Competitiveness

Destination competitiveness represents the ability of the destination to provide tourists with products that are distinctive, higher quality than those of other destinations which maximises the satisfaction level and sustain this outcome [1]. ST helps destinations increase their competitiveness [12].
The literature review yielded Figure 1, a conceptual framework to illustrates how bringing smartness at the destination leads to economic benefits. All the stakeholders supply side and demand side (tourism consumers) are networked together through various digital platforms. The supply side provides the necessary investments to bring technology and human capital (leadership). Smart Destination competitiveness is increased through better destination marketing, agile management, big data analytics and quality of life and wellbeing of all the stakeholders.

This leads in achieving greater economic benefits for the destination and efficiency of these factors.
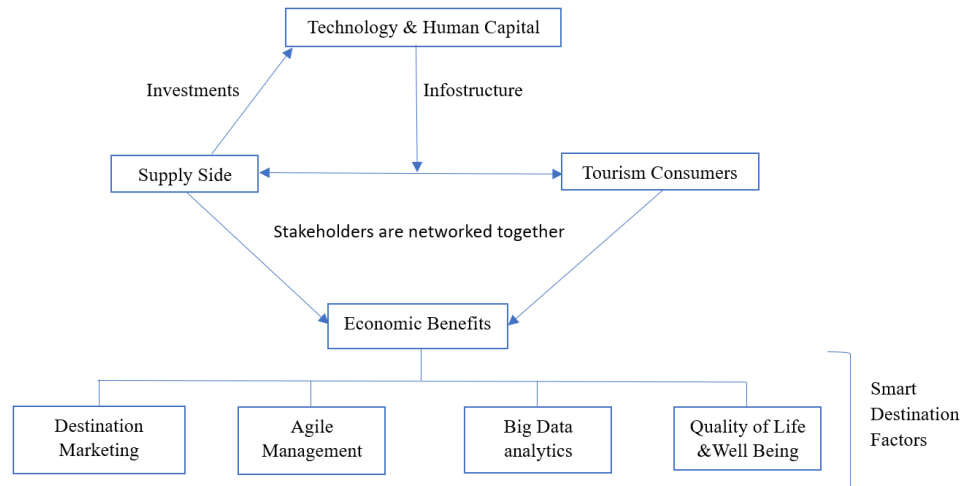
Figure 1: Conceptual framework Smart Tourism for Economic Growth

Destination Marketing benefits by using immersive technologies to provide businesses opportunities to engage with customers through mental imagery and stimulated presence leading to increased sales and brand awareness [28]. Networking of stakeholders and tourists enables the process of co-creation. AI algorithms and big data analytics help tourism businesses to gain insights on customer behaviour and preferences. Social media platforms help in retargeting customers by precisely addressing their needs according to desired demographics and lifestyle. This results in greater satisfaction and loyalty with increase in customer engagement [7]. Generative AI, such as chat GPT, provides an efficient marketing tool with automated intelligence that disseminate personalised information, generate itineraries and handle customer services in a swift way [33]. The personalised services use real time data and greater level of engagement leading to higher satisfaction for the tourists. This results in increased tourism expenditure, that translates to a higher level of income and output [3].

Agile management requires active participation, real-time information, posting reviews and sharing experiences to empower tourists to improve their experience [13, 9]. Innovation in marketing and use of modern technologies help in building increased destination appeal [29]. Chang [10] suggests that perceived value and use of smart tourism

technologies leads to a memorable tourist experience. That has positive effect on destination image and stimulate intention to revisit and recommend. Therefore, the use of ST technologies helps in building destination appeal, increases the level of satisfaction, improves destination image and creates destination loyalty. Replacing non-tradition methods of marketing with modern technologies that are cost effective leads to greater return on investment [33]. These smart technologies help businesses, by reducing their operational costs and increasing their efficiency by supporting the entire network [7].

Big data analytics supported by smart technologies collect a large amount of data through social media platforms and sensory devices from consumers and multiple data sources and analyse dynamically [36, 5]. The access to this data provides different insights to the service providers on consumer behaviour, patterns of consumption and help in demand forecasting [39]. Destinations and tourism organizations can increase their competitiveness by providing consumers with better quality of services.

The quality life of local residents at the destination is improved by networking of stakeholders and the process of co-creation leading to better optimization of resources at the destination [23]. Adopting ICTs help not only by stimulating innovation and economic development at the destination internally but also make it a focal point for the nearby destinations leading to regional growth [14]. Increase in efficiency and productivity creates healthy atmosphere and attracts better investment opportunities.

4   Conclusion and Discussion

This study conceptualises the role of ST for the destination economic growth. Based on a comprehensive search and a critical review of literature, a conceptual framework was formed to explore how Smart Tourism supports economic growth. It was found that Smart Tourism acts as a catalyst by networking different stakeholders together, to engage in the process of value co-creation. That enhances the destination competitiveness by providing innovative procedures and solutions. This leads to attaining economic benefits through reducing operational costs, increasing efficiency of production, improving local employment and encouraging higher tourist spending. This conceptual framework will be

further examined in the future research and will be validated using multiple case studies. The conceptual framework lays a critical foundation to further investigate on the relation of economics and smart tourism.

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Socio-Technical Ecosystem Change: Comparing Digital Networks of Tourism Destinations

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Abstract. The tourism industry is undergoing a digital transformation, with smart tourism as its core approach. The transformation extends beyond adopting technology to digitise processes and involves deep structural changes and redefining actors' relationships. At its core, the digital transformation represents a change in the socio-technical ecosystem—a complex interplay of tourism actors and technologies. A holistic understanding of the ecosystem is essential for effective, strategic, and collaborative destination governance that leverages technology to foster smart tourism. While theoretical models of smart destination structures provide useful frameworks, empirical validation and comparative research are necessary to assess how digital transformations unfold in different contexts. This research explores similarities and differences in the socio-technical ecosystems of six destinations in Spain and Mexico by analysing stakeholders' digital networks—a core element of these ecosystems. Using hyperlink analysis of connected websites, this study identifies patterns within the data and offers grounded hypotheses and directions for future research.

Keywords: tourism destination, socio-technical ecosystem, digital network.

1 Introduction

The tourism industry is undergoing a digital transformation, with the development of smart destinations at its core. This transformation involves profound structural changes beyond merely adopting technology to digitalise processes and improve operational efficiency. Specifically, the shift toward smart tourism redefines the role of technology in tourism, reimagines the use of tourism data, transforms value co-creation

among stakeholders, fosters collaborations, and influences the governance and management of destinations [1].

At its core, digital transformation represents a shift in the socio-technical system—the composition of the system (tourism stakeholders and technologies) and their interconnections [2]. The emergence of new actors or technologies within the system can significantly alter its structure and relationships. Due to the interdependency of its elements, where even minor changes in composition can lead to significant transformations across the entire system, it can be viewed as an "ecosystem" in which communities of interacting actors operate within their environments [3].

Understanding the structure and relations of the socio-technical ecosystem (STE) is of fundamental importance for strategic, collaborative, and technology-based destination governance. The transition to smart tourism goes beyond adopting technologies; it involves organisational factors and needs governance to integrate and coordinate stakeholders effectively [4, 5, 6]. Understanding the STE creates opportunities to identify key technologies that play central roles in the STE, evaluate the destination's dependency on specific technologies, identify gaps in technology adoption, and recommend technologies used by successful destinations of a similar type.

This research aims to explore the similarities and differences in STEs across various destinations by comparing the stakeholders' digital networks, which are core elements of the ecosystems. The study identifies patterns in the configurations of the destinations' STEs, formulates grounded hypotheses (based on observed data), and suggests directions for future research.

2   Literature review

Socio-technical transformations differ from technological transitions by encompassing profound changes in the system structures, user practices, and institutions alongside technological developments [7]. The transformation of a destination depends not only on technological advancements but also on how technology is adopted and utilised by ecosystem actors [4]. The evolving roles of destination management organisations (DMOs) increasingly focus on building ecosystem relations, connecting with "external" stakeholders, and creating shared value [8]. Tourism actors adjust their practices by collaborating with specific ICT

actors and adopting technologies, directly shaping the destination ecosystem structure.

The convergence of physical and digital systems increasingly characterises socio-technical transformations. The digital-network-based integration of tourism stakeholders, ICT providers, and technologies plays a vital role in these transformations [6]. A broader range of actors becomes relevant for the destination ecosystem, including non-tourism businesses [3, 5]. In particular, ICT actors, as suppliers of digital tools, are vital for both their technical capabilities and their potential to reshape the ecosystem. Evaluating the centrality of ICT actors and identifying the shared and differing connections of tourism actors with ICT actors is crucial for understanding the STE and formulating effective strategies for digital transformation.

Although theoretical models of smart tourism destination structures have been proposed [e.g., 3], empirical validation of these structural components is still needed. Furthermore, comparative research is essential to understand better how these structures evolve across destinations with different digital transformation processes. To advance the understanding of the similarities and differences of socio-technical ecosystems of different types of tourism destinations, this study is framed around the following research question: How do (a) the positions of ICT actors, (b) the relationships among tourism sectors, and (c) the connectivity characteristics of digital networks within socio-technical ecosystems differ across tourism destinations with varying level of smart tourism development and diverse socio-economic and geographic contexts?

3 Methodology

An exploratory research approach was adopted. It examined the composition and relationships of the socio-technical ecosystem through digital networks of organisational and institutional websites. Connecting them hyperlinks served as proxies for the relationships within the system [9]. The research used a convenience sample of six destinations and their tourism actors, marked by the available databases. Five destinations participated in the smart tourism destination diagnosis by SEGITTUR, a Spanish state-owned organisation. Two destinations have reached a "Smart Tourism Distinction" (level 4): **Donostia/San Sebastián**:

Spain, Gipuzkoa, urban coastal (city), N = 233; **Tequila**: Mexico, Jalisco, urban inland (city), N = 18. Three destinations had a lower level 3: **Cáceres**: Spain, Cáceres, urban inland (city), N = 112; **Debagoiena**: Spain, Gipuzkoa, urban and rural inland (region), N = 41 actors; **Goierri**: Spain, Gipuzkoa, urban and rural inland (region), N = 41. One destination did not participate in the certification: **Urola Kosta**: Spain, Gipuzkoa, urban and rural coastal (region), N = 109.

The destinations were represented by DMOs; tourism-related public bodies; natural and cultural resources; accommodations; events, sports and recreational activities; travel agencies, and other reservation services. In 2024, their websites were crawled using the web crawler Hyphe [9]. The web crawling detected the relations among the initial sample of tourism actors ("internal" network) and their connection to other entities discovered through web crawling ("external" network). The entities connected to the initial tourism actors were classified to discern the most referenced ICT actors. Furthermore, Social Network Analysis metrics were used to analyse the networks. Intersectoral relations were analysed through the number of links placed from one sector to another.

4   Findings

The most influential ICT actors in the socio-technical ecosystems did not vary across tourism destinations with different levels of smart tourism development and diverse socio-economic and geographic contexts. The analysis of the most linked ICT actors by tourism actors showed that all tourism destinations had the same leading ICT actors. Facebook.com, Google.com, and Instagram.com consistently occupied the top three positions, though in varying orders at each destination. Regardless of the region, five Spanish destinations shared nine of the top 10 ICT actors (Fig.1). Despite being geographically distant from Spain, Tequila shared five of the top 10 most linked ICT actors with Spanish destinations.

However, socio-economic and geographic contexts have conditioned, to some extent, tourism actors' choices beyond the core ICT structure. Thus, slight differences were observed between the destinations of different continents and sizes when half of the top 10 ICT actors of Tequila's destination differed from the bigger destinations in Spain. In the Travel Tech subcategory, "Tripadvisor" was the most linked actor in four destinations. In the other two, situated in rural areas rich in natural

parks and mountains, "Tripadvisor" was ranked second behind Wikiloc.com, a platform for discovering and sharing outdoor trails. Such differences show a possible influence of geographic characteristics (rural inland nature-based vs. cities with events and recreation agendas) on the position of ICT actors in the ecosystems.
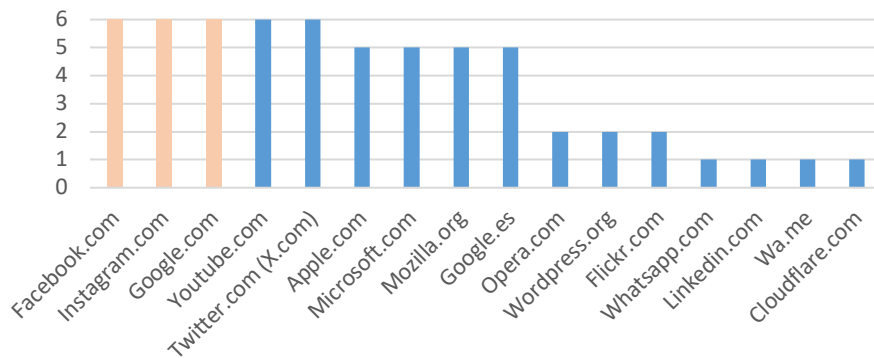
Fig. 14. Common influential ICT actors of six tourism destinations. The number represents how many destinations each ICT actor ranks among the top 10 most referenced. Orange highlights indicate the ICT actors that appear in the top 3 for each destination.

Regardless of the destination type, the support provided by DMOs to the accommodations sector emerged as the most prominent intersectoral relationship. In all ecosystems, DMOs placed more links to accommodations than to any other tourism sector. On average, this relationship accounted for 24% of the established connections within the destinations' ecosystems. This pattern was particularly pronounced in the ecosystem of Tequila (Mexico), where it constituted 41% of all connections. In contrast, in Spanish destinations, the proportion ranged from 8% to 31%.

The socio-economic and geographic context had some relevance for the extent of diversification of intersectoral relations. In general, Spanish destinations had more varying types of intersectoral relations than the destination in Mexico. DMOs established 71% of the ecosystem's connections in Tequila, while at Spanish destinations, more other sectors were taking an active role in destination ecosystems and DMOs' share was, on average, 37%.

Among the studied destinations, the distinguished smart destination of Donostia/San Sebastián stood out for its highly diverse intersectoral relationships. It also featured a notably active accommodations sector,

contributing 40% of the ecosystem's connections and maintaining extensive links with "events, sports, and recreational activities" and "natural and cultural resources." However, the distinguished smart destination in Mexico exhibited less diversity and lacked similarly active non-DMO sectors.

The connectivity qualities of destinations' digital networks did not appear to be directly influenced by their level of smart tourism development (Table 1). Clear differences were observed only between Donostia/San Sebastian (Gipuzkoa, level 4) and Cáceres (level 3), with Donostia demonstrating a more advanced stakeholder network, while other destinations did not follow this pattern. Despite lacking a smart destination distinction, the remaining destinations in Gipuzkoa showed results similar to those of Donostia. In addition to the higher number of connections per actor, there was greater reciprocity in the links between tourism actors, as well as a stronger tendency to form localised clusters of collaboration, as reflected in the higher average clustering coefficient. These findings suggest that socio-economic factors, specific to each region and country, may play a more significant role in shaping the foundational features of a destination's socio-technical ecosystem than its smart tourism development level.

Table 10. Connectivity qualities of tourism destinations' digital networks

	DSS (n=233)	CAC (n=112)	UK (n=109)	DBG (n=41)	GOI (n=41)	TEQ (n=18)
Connections per actor in the "internal" network	2.7	1.1	2.9	2.7	2.8	0.9
Connections per actor ("internal" & "external")	1.5	1.4	1.7	1.5	1.5	1.3
External/internal network size ratio	31	28	17	41	38	6
Disconnected actors	19%	48%	7%	15%	7%	17%
Average clustering coefficient	0.197	0.104	0.459	0.310	0.304	0.094
Reciprocity level	18%	9%	18%	33%	36%	6%

Note. Tourism destinations: DSS = Donostia/San Sebastián, CAC = Cáceres, UK = Urola Kosta, DBG = Debagoiena, GOI = Goierri, TEQ = Tequila; n refers to sample size.

5   Discussion and future research

The data analysis led to the development of grounded hypotheses.
1. Varying tourism destinations are similar in a fundamental ICT structure. Similarities were found across destinations with varying

progress in smart tourism development and socio-economic and geographic contexts. The structure was shaped by global ICT actors such as multifunctional web platforms and social media. This consistency might be because these platforms provide essential services that are crucial for tourism across all stages and contexts of development. However, such dominance can create a "homogeneity" that shapes online spaces to align with the interests of major platforms, acting as "gate-keepers."

2. The socio-economic context, to a greater extent, shapes the basic features of the socio-technical ecosystem than the level of smart tourism development. The context had some relevance for the inter-sectoral relations diversity, network connectivity level, and the choices of ICT actors to connect with. The destinations of the same administrative territory showed very similar digital network properties, while they had different levels of smart tourism development. The networks of different countries showed differences in the connected ICT actors (beyond the common "core").

3. Destinations similar in geographic characteristics establish similar relations in the socio-technical ecosystem. While destinations have a common fundamental structure, their geographic qualities may shape intersectoral relations and tourism actors' relations with ICTs. Preferences for specific types of travel technology suggest that certain technologies may be well-suited to specific types of destinations. Understanding these preferences could help formulate tailored recommendations for similar destinations.

Future research should gather more data from diverse destinations that vary by country, region, size, and level of smart destination development and introduce additional variables to describe these destinations more comprehensively. Furthermore, additional variables should be incorporated to enhance the comprehension of network structures. Finally, digital representations beyond organisational websites, such as social media profiles or listings on distribution platforms, can be included.

Effective governance requires long-term planning that aligns stakeholder efforts with technological capabilities, ensuring cohesive collaboration between tourism providers, ICT actors, and public institutions. Flexible governance frameworks must integrate emerging technologies without disrupting stakeholder alignment. Empirical studies are essen-

tial for evaluating digital transformations and identifying effective strategies under varying conditions, promoting sustainable and inclusive growth.

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Section 7: Experience Markets

Exploring the impact of searching and booking time investments on customer's satisfaction with hospitality services

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Abstract. This study investigates the impact of time spent in the information search and booking phases on consumer satisfaction during the service experience within the hospitality industry. Using Process modeling tool (observed variable OLS and logistic regression path analysis modeling tool), the research explores how prolonged engagement in these pre-service activities can lead to heightened expectations, resulting in decreased satisfaction when experiencing the service. The study also examines the moderating role of emotional experience during the ser-vice, finding that positive experiences can mitigate the negative effects of extend-ed pre-service time by helping confirm consumer expectations. Data were collect-ed from 1,000 tourists in Istanbul, Türkiye, across various 4-star and 5-star hotels and restaurants. The findings suggest that optimizing digital platforms to re-duce the time invested in them is critical for enhancing satisfaction. Additionally, the importance of fostering a positive emotional experience during the service is highlighted as a key strategy for confirming previous expectations and maintaining consumer satisfaction. This research contributes, both theoretically and practically, to the understanding of how different stages of consumer behavior interact to form satisfaction, offering insights for improving service quality and consumer engagement in the hospitality industry.

Keywords: Consumer satisfaction, Searching time, Booking time, Information overload, Emotional experience.

1   Introduction

In the hospitality industry, the consumer journey is increasingly shaped by digital platforms that offer a wealth of information and booking options in the hospitality services. While this abundance of choice empowers consumers, it also presents significant challenges. Prolonged search and booking phases can create heightened expectations, which, when unmet during the service experience, result in consumer dissatisfaction. This research investigates the impact of time spent in the information search and booking phases on consumer satisfaction on the hospitality services, using Expectation-Disconfirmation Theory (EDT) as a theoretical framework. Additionally, we explore how positive emotions during the service experience can mitigate dissatisfaction caused by long pre-service phases, drawing on the Theory of Emotions [1].
According to Expectation-Disconfirmation Theory (EDT), consumer satisfaction is determined by the relationship between prior expectations and actual experiences. If the actual service fails to meet these expectations, negative disconfirmation occurs, leading to dissatisfaction [1], and in the context of this study, the prolonged time spent searching for information and booking hospitality services amplifies consumer expectations.
Moreover, the Theory of Emotions plays a critical role in understanding how satisfaction is shaped during the service encounter. When consumers feel positive emotions during their service interaction, these emotions can help mitigate the dissatisfaction caused by prolonged search or booking times. This aligns with the concept that emotions play a pivotal role in recalibrating consumer perceptions, particularly when expectations have not been met [2].
Despite the well-established frameworks of these theories, there remain gaps in the literature, particularly regarding the impact of time invested in pre-service activities like search and booking. The objective of this research is to explore the dual influence of search and booking time on consumer satisfaction through the lens of Expectation-Disconfirmation Theory, while also examining the moderating effect of emotional experiences during the service phase. By understanding how these factors interact, we aim to offer insights into optimizing pre-service digital experiences and enhancing emotional engagement during the service, contributing to improved satisfaction and consumer engagement in the hospitality industry.

2   Literature review and hypothesis development

At the heart of this study is Expectation-Disconfirmation Theory (EDT), which has been widely applied to consumer behavior research. According to EDT, satisfaction is determined by the gap between consumers' pre-service expectations and the actual service experience [1]. When actual experiences fall short of expectations, negative disconfirmation occurs, leading to dissatisfaction. In the context of the hospitality industry, the time spent searching for information and booking services can significantly influence these expectations [2].

Consumers today engage deeply with online content before making travel-related decisions. The more time they invest in reviewing options, reading online reviews, and comparing services, the higher their expectations become [3]. This relationship between extended pre-service activities and heightened expectations has been documented in previous research [4,3]. However, when the actual service experience fails to meet these expectations, dissatisfaction is inevitable [5]. This is particularly true in digital contexts, where the availability of vast amounts of information leads to information overload, making it difficult for consumers to process and manage expectations effectively.

Thus, we propose the following hypotheses:

H1a: Increased time spent in the information search phase has a negative effect on consumer satisfaction during service encounter.

H1b: Increased time spent in the booking phase has a negative effect on consumer satisfaction during service encounter.

While expectations play a pivotal role in shaping satisfaction, emotional experiences during the service encounter are equally critical. The Theory of Emotions suggests that emotions felt during service interactions profoundly influence consumer perceptions and satisfaction [2]. Positive emotional experiences can act as a buffer, mitigating dissatisfaction caused by unmet expectations, particularly when the service experience delivers pleasant and unexpected moments of delight.

In the hospitality industry, where the service encounter is often laden with emotional meaning, positive emotions can override prior frustrations. For example, a consumer who spent excessive time searching for a hotel or restaurant might develop high expectations. If the service itself provides an emotionally enriching experience—whether through exceptional customer service, personalized attention, or a memorable atmosphere—these emotions can recalibrate the consumer's perception,

leading to overall satisfaction despite earlier frustrations [6]. Thus, we propose the following additional hypotheses:

H2: A positive (vs. negative) emotional experience during service encounter has a positive effect on consumer satisfaction at that stage.

H3a: A positive emotional experience during service encounter reduces the negative effect of time spent in the information search phase on consumer satisfaction during service encounter.

H3b: A positive emotional experience during service encounter reduces the negative effect of time spent in the booking phase on consumer satisfaction during service experience.

Satisfaction not only influences a consumer's immediate experience but also has broader implications for long-term engagement with a brand or service. Previous research has shown that satisfied consumers are more likely to engage in positive behaviors such as repeat visits, loyalty, word-of-mouth advocacy, and digital engagement [7]. In the context of this study, we posit that consumer engagement is closely tied to satisfaction during the service encounter. This relationship is particularly important in the hospitality industry, where digital interactions, social media engagement, and online reviews play a crucial role in shaping consumer perceptions. Thus, we propose:

H4: Increased consumer satisfaction during service enjoyment has a positive effect on consumer engagement.

3   Methodology and results

This research employed a survey methodology to explore how time invested in the search and booking phases affects consumer satisfaction and how emotional experiences during the service mitigate dissatisfaction. Data were collected between 20 November and 30 December 2023 from 1,000 tourists in Istanbul, Türkiye. The sample included 600 hotel guests and 400 restaurant patrons. Both international and domestic tourists were surveyed to capture diverse consumer behaviors. The survey measured key variables across the consumer journey: Search and booking time (time was categorized into five groups, less than 10 minutes to more than 60 minutes, based on prior studies) [8]; Emotional experience (participants rated their emotional experience (positive or negative) during the service encounter) [6]; Satisfaction (measured on a 5-point Likert scale, from "very dissatisfied" to "very satis-

fied") and; Consumer engagement (post-consumption engagement behaviors such as word-of-mouth advocacy and social media interactions were assessed) [9].

To test the hypotheses, process modeling (observed variable OLS and logistic regression path analysis modeling tool), was used to analyze direct and moderating effects [10]. This allowed us to explore the relationships between search and booking times, satisfaction, emotional experiences, and engagement. The preliminary results confirmed key hypotheses. Firstly, prolonged search and booking times negatively affected consumer satisfaction. Consumers who spent more time in these phases reported lower satisfaction during the service encounter, in line with Expectation-Disconfirmation Theory (**H1a** and **H1b**). Secondly, positive emotional experiences significantly improved satisfaction. Consumers who experienced positive emotions during service reported higher satisfaction levels (**H2**). Thirdly, Emotional experiences mitigated the negative impact of long search and booking times. Positive emotions during the service buffered dissatisfaction caused by extended pre-service activities, supporting the Theory of Emotions (**H3a** and **H3b**). And finally, higher satisfaction led to increased consumer engagement, with satisfied consumers more likely to engage in positive post-consumption behaviors, such as recommending the service or interacting with the brand online (**H4**).

4   Conclusions

This study has investigated the relationship between the time spent in the information search and booking phases and its impact on consumer satisfaction during the service experience within the hospitality industry. The analysis revealed that prolonged engagement in these pre-service phases can lead to decreased satisfaction, primarily due to heightened consumer expectations that are difficult to meet during the service encounter. However, the research also demonstrated that positive emotional experiences during the service can mitigate these negative effects, recalibrating consumer perceptions and enhancing overall satisfaction. Firstly, the findings suggest that hospitality businesses should streamline their digital platforms, particularly in the search and booking phases, to minimize decision fatigue and frustration. Simplifying user interfaces, reducing the number of steps required to complete a booking, and curating relevant information can reduce the time consumers

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spend in pre-service phases, thereby mitigating the development of unrealistic expectations. Secondly, under our knowledge, it is essential for businesses to ensure that the information provided during the pre-service stages is clear, concise, and realistic. Offering accurate depictions of services, pricing transparency, and curated options can prevent the formation of expectations that are difficult to meet during the actual service experience. This will help businesses align consumer expectations more closely with the service they are able to deliver, reducing the risk of negative disconfirmation. Finally, positive emotional experiences during the service encounter were shown to buffer the negative effects of prolonged search and booking times. Therefore, hospitality managers should focus on creating emotionally enriching service environments, by training staff to deliver personalized, empathetic, and memorable service encounters. Such emotional engagement can realign consumer perceptions and enhance overall satisfaction, even when initial expectations are unmet.

From a theoretical perspective, this study extends the application of expectation-disconfirmation theory and the theory of emotions to the context of the hospitality industry, emphasizing the interactive nature of pre-service activities and emotional experiences. While these theories are well-established, this research offers new insights by demonstrating how digital engagement in pre-service phases, particularly time spent searching for information and booking services, amplifies expectations. The study also highlights the importance of emotions as a mitigating factor during the service experience, which has been less explored in previous hospitality research.

From a managerial perspective, businesses could implement customizable interfaces that allow users to filter based on their preferred decision-making style. For instance, "quick decision" modes could offer simplified searches with fewer but more targeted options, while "detailed comparison" modes could cater to users who want to explore more options with in-depth comparisons. Additionally, emotional priming strategies can be used before the service to elevate consumer emotions and smooth the transition from the digital pre-service phase to the actual service experience. For example, sending emotionally engaging content (e.g., welcome videos, personalized recommendations) after booking. Moving forward, future research should explore how these dynamics vary across different geographic contexts, since this study was based solely on Turkish destinations. Additionally, future studies could also

delve deeper into the role of consumer emotions, particularly in the context of rationality versus emotional responses and how these shape long-term engagement and loyalty.

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Work, Wander, Repeat: How Digital Nomads Are Shaping Tourism in a Post-Pandemic World

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Abstract. Despite the growing interest in digital nomadism, there is a significant gap in understanding its evolving landscape within the global context. Hence, this study explores the dynamics of the digital nomad lifestyle as well as their challenges and opportunities. Through topic modelling analysis of 11,210 Instagram posts tagged with #digitalnomad and #digitalnomadvisa, the research identifies key mobility aspects within the digital nomad community. Findings highlight the significance of unlocking the strategy of geoarbitrage, and the intersection of mobility and lifestyle. The study also reveals insights on entrepreneurship and remote work strategies. Finally, the analysis uncovers a trend towards personal transformation, where digital nomads experience significant growth through autonomy, community engagement, and the challenges of a nomadic lifestyle.

Keywords: digital nomad; nomadic lifestyle; remote work; mobility; geo-arbitrage

1   Introduction

The COVID-19 pandemic has reshaped the profile of digital nomads, broadening it from primarily young freelancers and entrepreneurs to a more diverse group that now includes salaried employees, families, and a wider demographic of mobile workers [1, 2]. Enabled by digital technologies and the rise of remote work, digital nomads are individuals seek to balance work and leisure while living in low-cost regions while earning higher wages from remote work [3]. Often portrayed as young avant-garde individuals, digital nomads are seen as individuals who have broken free from traditional office norms, choosing instead to travel the world and work remotely on a laptop from the beach or in cafes in idyllic locations. However, the concept of digital nomads has

increasingly broadened, encompassing lifestyles and practices that go beyond this initial stereotype [1]. The post-pandemic nomad lifestyle has created a new category of long-term visitors who contribute to local economies in unique ways, blending their professional and personal lives across different destinations. Stakeholders such as local governments, tourism managers, and service providers are faced with both challenges and opportunities as they adapt to this evolving demographic. By examining the impact of geoarbitrage and long-term mobility on tourism destinations, the research explores the challenges and opportunities posed by digital nomads with their work-leisure hybrid lifestyle. As digital nomads continue to blur the lines between tourists, residents, and workers, destinations are encouraged to create new dynamics in tourism and remote work ecosystems [4] so as to offer guidance catering to the unique needs of digital nomads, such as reliable internet, coworking spaces, and community-building activities.

2   Theoretical background

With the widespread availability of digital technology and interconnectivity, mobility has become more feasible than ever, empowering digital nomads to seamlessly transition between destinations [5]. In the context of digital nomadism, mobility extends beyond mere geographical displacement. It encompasses social and cultural dimensions, highlighting how individuals navigate and interact with diverse environments and economies while remaining tethered to global networks [6]. Turned into a lifestyle, mobility—as fluid and transient status of modernity [7]—allows digital nomads the conscious avoidance of traditional constraints such as permanent housing or traditional offices.
In the post-pandemic world, mobility is also supported by policy changes such as digital nomad visas. The growing adoption of digital nomad visa programs [8], aimed at attracting long-term, skilled remote workers, has further facilitated mobility by providing legal frameworks that offer flexibility for extended stays while working remotely [9]. This allows digital nomads to adjust their locations in accordance with personal aspirations, lifestyle choices, or the pursuit of financial efficiency through geoarbitrage [10].
Digital nomads apply geoarbitrage—the practice of living in low-cost regions while earning higher wages from remote work—to stretch their

income and achieve higher standards of living [11]. This practice is crucial to their lifestyle, allowing them to enjoy financial freedom while traveling [12]. In digital nomadism, geoarbitrage has been traditionally associated with young entrepreneurs and freelancers [3]. However, the pandemic-induced shift to remote work has broadened this demographic with salaried employees and professionals now leveraging geoarbitrage to improve their quality of life while maintaining stable income streams [2]. This aligns with the FIRE (Financial Independence, Retire Early) movement, where individuals seek to reduce living expenses and maximise savings, potentially to achieve financial independence more rapidly [13].

Their ability to stay for extended durations without the need to commute to a physical office makes them unique participants in the tourism ecosystem [14]. This work-leisure hybrid behaviour [15] creates a new demand for tourism services that cater to long-term, tech-savvy residents who need a mix of professional infrastructure and leisure experiences. Tourism destinations have recognised this trend and adapted to attract digital nomads by promoting the development of their service infrastructure beyond offering digital nomad visas such as coworking spaces [16,17]. These services are key to enabling digital nomads to fully engage in geo-arbitrage, making it possible to work efficiently from anywhere while managing their financial interests [18].

As the digital nomad community grows, understanding mobility patterns and the practice of geoarbitrage has become a central aspect for tourism destinations. This shift not only has a major impact the dynamics of remote work but has also redefines the traditional distinctions between tourists, residents, and workers [4]. Digital nomads, as work-leisure hybrids [15], require therefore destinations to adapt to their unique needs. This study seeks to explore how the post-pandemic digital nomad lifestyle, and financial optimization, driven by mobility and geoarbitrage, influenced tourism dynamics in search of a balance work, travel, and financial optimization.

3   Methodology

To explore mobility and geoarbitrage within the digital nomad community, this study analyses Instagram posts using the hashtags #digitalnomad and #digitalnomadvisa shared by Instagram users (self-identified digital nomads). Instagram was chosen for data exploration due to

its widespread use among digital nomads [10], making it an ideal platform where they share their opinions, experiences, and travel-related content. The #digitalnomad hashtag captures content related to the digital nomad lifestyle, while #digitalnomadvisa specifically highlights posts that discuss various destinations, visa options, and associated attractions.

Data was extracted using Apify in May 2024. The collected data included date of post, captions, post URLs, and number of likes and comments. Recognizing the potential shifts in perceptions and behaviours due to the COVID-19 pandemic, the research purposely focused on posts from 2023 onwards to ensure relevance to the current era. In total, 8,508 posts tagged with #digitalnomad and 2,702 posts tagged with #digitalnomadvisa were extracted.

The collected data underwent several pre-processing steps to ensure its suitability for subsequent topic modelling analysis. BERTopic, an emerging topic modelling technique that leverages BERT (Bidirectional Encoder Representations from Transformers) to generate high-quality embeddings for textual data, was employed. BERTopic utilizes a sentence-transformers model and applies a class-based term frequency-inverse document frequency (c-TF-IDF) algorithm. The higher the c-TF-IDF value for a term, the more it signifies the relevance of that term to its respective topic.

4   Results and discussion

Based on the extracted posts, BERTopic identified 27 distinct clusters, which were organized into five main dimensions: 1) entrepreneurship and remote work strategies (n=4), 2) unlocking the strategy of geoarbitrage (n=9), 3) travel experiences and tourism destinations (n=7), 4) crossroads of mobility and lifestyle (n=5), and 5) personal transformation and community building (n=2). Figure 1 outlines a summary of the five main aspects, along with the strategies and expectations shared by self-identified digital nomads on Instagram.

Figure 15. An overview of the various aspects of digital nomad lifestyle
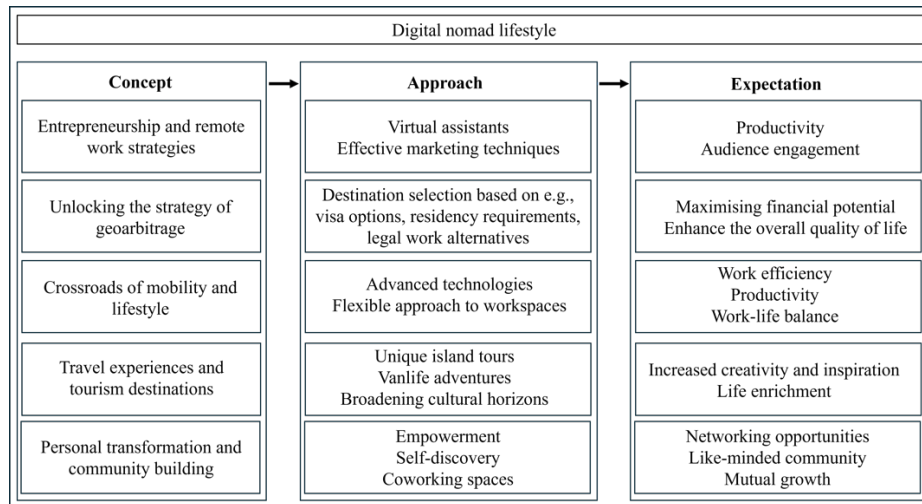
Overall, the digital nomad lifestyle flourishes at the intersection of entrepreneurship and remote work strategies, where individuals harness various tools to succeed in their ventures. This aspect explores issues such as how leveraging virtual assistants can boost productivity and explores effective marketing techniques vital for audience engagement. This aligns with the principles of the gig economy [1], where flexibility and multiple income sources are crucial for sustaining a mobile lifestyle. Meanwhile, geoarbitrage emerges as a compelling strategy for maximising financial potential by living in lower-cost regions while earning from higher-cost markets. This aspect centres on visa options, detailing application processes, residency requirements, and legal work alternatives for digital nomads who expatriate [9]. Essentially, insights on strategically selecting destinations not only based on economic factors but also on the availability of tourism infrastructure and cultural experiences can significantly enhance the overall quality of life for digital nomads.

Furthermore, the synergy between mobility and lifestyle allows for an exploration of advanced technologies that improve work efficiency, all while maintaining a balanced life [4]. This interplay not only fosters productivity but also encourages a more flexible approach to workspaces, enabling individuals to adapt their environments to suit both professional and personal needs. By exploring travel experiences and

ideal tourism destinations, such as unique island tours and vanlife adventures, remote workers can enhance their lifestyle while broadening cultural horizons, which is closely linked to the mobility paradigm [6]. Such experiences can lead to increased creativity and inspiration, ultimately enriching both their personal lives and professional outputs. Finally, the topics reflect a recent and emerging trend centred on personal transformation, encompassing aspects such as self-actualization, personal growth, and overall well-being. Narratives from those who have embraced this lifestyle reveal the empowerment and self-discovery that come with it. Community building through coworking spaces [16] and networking opportunities enriches the nomadic experience, emphasizing the importance of connecting with like-minded individuals for mutual growth and development.

5   Conclusion

Overall, this research highlights that digital nomads thrive at the intersection of remote work and entrepreneurship, utilising strategies like geoarbitrage to maximise financial potential and improve quality of life through strategic destination choices. Personal growth and community building are also emphasised, showcasing the role of coworking spaces and networking in enriching the nomadic lifestyle. The findings provide significant theoretical and practical contributions to the understanding of digital nomadism in the post-COVID-19 landscape based on relevant Instagram posts. Theoretically, it expands upon existing literature by situating digital nomadism within the broader frameworks of mobility and geoarbitrage, illustrating how these concepts intertwine to redefine traditional work and travel paradigms. The identification of distinct clusters through topic modelling further enriches the comprehension of diverse narratives within the digital nomad community. Practically, the findings underscore the need for tourism destinations and service providers to adapt to the evolving demands of digital nomads. By recognizing the unique blend of work and leisure that characterizes this demographic, stakeholders can tailor their offerings—ranging from coworking spaces to visa facilitation—to better serve the needs of long-term, tech-savvy residents. This not only enhances the tourist experience but also fosters local economies by attracting skilled remote workers who contribute financially to their host locations.

Yet, this study is not without its limitations. First, relying on Instagram as the sole data source may not fully capture the diverse experiences of all digital nomads. Additionally, the focus on posts from 2023 onwards may overlook earlier trends and shifts in the digital nomad landscape influenced by the pandemic. Looking ahead, future research should explore narratives across various digital platforms and incorporate interviews or surveys to gain deeper insights into the motivations and challenges faced by digital nomads. Furthermore, it would be beneficial to delve deeper into the narratives surrounding each identified aspect, as well as to examine other relevant hashtags. By exploring how these dimensions influence the lived experiences of digital nomads, this working paper can gain a more nuanced understanding of their motivations and challenges. Additionally, examining the long-term implications of digital nomadism on local cultures and economies will be crucial for developing sustainable models that benefit both nomads and host communities. Through this exploration, this research aims to contribute to a more holistic understanding of this dynamic lifestyle and its implications for the future of work and travel.

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Exploring the Utility of Social Media in Promoting Pro-environmental Norms Among Nature-Based Tourists

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Abstract .outh Africa's rich biodiversity and nature-based tourism face significant conservation challenges, including habitat fragmentation, invasive species, and poaching. This study explores how Information and Communication Technologies (ICTs), mainly social media, can activate pro-environmental personal norms among tourists to support conservation in South Africa. Drawing on the Norm Activation Model (NAM) and the Theory of Planned Behaviour (TPB), the research aims to understand how social media platforms influence tourists' conservation attitudes and behaviours. A mixed-methods approach will be employed, combining a netnographic analysis of social media content and a survey of domestic and international tourists. The study expects to reveal that social media plays a crucial role in shaping personal norms and encouraging pro-environmental behaviours, such as sustainable tourism practices, recycling, and resource conservation. This research will fill a critical gap in understanding ICT's role in conservation within an African context and offer practical recommendations for leveraging social media to influence pro-environmental behaviours and enhance sustainable tourism and conservation efforts in South Africa.

Keywords: Information and Communication Technology, Social Media, Personal Norms, Conservation.

1   Introduction

Environmental sustainability is critical in South Africa, a country known for its rich biodiversity and numerous nature-based tourism destinations. However, iconic species like the African elephant and rhinoceros are under severe threat, with poaching fueled by the lucrative black market for rhino horn and exacerbated by corruption within wildlife management [17]. These challenges are compounded by environmental degradation from urbanisation, pollution, and illegal activities like sand mining, contributing to South Africa''s ecological deficit and straining

its natural resource base [18][19]. Socio-economic disparities further hinder conservation efforts, with urban residents typically showing greater environmental awareness than rural communities, who often depend on natural resources for their livelihoods [20]. This disparity underscores the need for inclusive strategies that balance ecological sustainability with community engagement and economic realities. While traditional conservation efforts have focused on policymaking and industry regulation, a growing need exists to engage tourists directly in pro-environmental behaviours. This research explores how information and communication technology (ICT), mainly social media, specifically Facebook, TikTok and Instagram, can activate pro-environmental personal norms among tourists, thereby supporting conservation efforts in South Africa.

The study will adapt the theoretical framework used by [1], which investigates the role of informational, normative, and emotional cues in activating personal norms. Specifically, social media presents a far-reaching platform for promoting conservation behaviour. Pro-conservation behaviour from tourists includes but is not limited to making financial contributions, voluntourism and changes in personal sustainable behaviour, such as recycling and reducing water usage.

Research indicates that personal norms, which are feelings of moral obligation to act pro-environmentally, play a crucial role in shaping behaviour. As a source of information, social media has immense potential to influence the formation of norms that impact pro-environmental behaviours. Moreover, conservationists could use ICT, especially social media, to influence personal norms and lead to sustainable behaviour that ultimately contributes to conservation among tourists.

2   Background

Integrating Information and Communication Technologies (ICTs) into conservation efforts is increasingly seen as a vital approach to promoting sustainable nature-based tourism and environmental sustainability [2]. ICTs, particularly social media, facilitate information sharing and awareness, engaging both tourists and local communities in conservation efforts [3]. These technologies enable the monitoring of environmental impacts and encourage sustainable practices, ensuring tourism contributes positively to environmental and community development. User-generated content on social media plays a significant role in promoting pro-environmental behaviour [4]. Pro-environmental behaviour is also referred to using various terms such as, but not limited to, green behaviour, environmentally sustainable consumer behaviour, and eco-friendly behaviour or consumption, and it has become a hot topic among tourism academics and practitioners [21]. Social media enhances subjective norm perception, fostering pro-environmental attitudes [5]. Communication campaigns highlighting environmental progress further encourage eco-friendly behaviour [6]. The Value-Belief-Norm (VBN) framework links personal values with pro-environmental norms, influ-

encing behaviour [7]. Green advertising and descriptive norms also promote sustainable actions [8]. Normative influences from family and friends affect adolescent pro-environmental behaviour [9], while the Value-Identity-Personal Norms model predicts adult behaviour [10]. In South Africa, the effects of climate change, including droughts and floods, highlight the importance of ICTs, such as social media, for conservation efforts [11]. Despite these advancements, the role of social media in influencing nature-based tourists'' conservation behaviour remains underexplored. This study addresses this gap, adapting findings from [12] to the South African context to explore how social media can enhance conservation strategies involving eco-tourists, scientists, and local authorities [13].

3 Purposw

The purpose of this study is:

1. To quantitatively explore how the effective use of social media influences tourists' norms towards conservation attitudes and behaviour.
2. To explore to which extent local influencers affect the residents' pro-environmental behaviour and defence of their own environment.
3. To analyse how effectively using ICTs, specifically social media, influences tourists' norms towards conservation attitudes and behaviour through a qualitative content analysis of social media data.
4. To develop recommendations for using social media to influence tourists' personal norms.

4 Theory

Vital theoretical frameworks must be examined to investigate how social media influences nature-based tourists' personal norms towards conservation. The Theory of Planned Behaviour (TPB) and the Norm Activation Model (NAM) provide foundational insights into conservation behaviour.

Integrating the Theory of Planned Behaviour (TPB) and the Norm Activation Model (NAM) provides a comprehensive framework to address the complexity of promoting pro-environmental behaviour among nature-based tourists through social media [22]. NAM emphasises moral obligations and personal responsibility, activated through awareness of consequences (AC) and ascription of responsibility (AR). At the same time, TPB focuses on behavioural intention shaped by attitudes, subjective norms, and perceived behavioural control (PBC) [23]. Social media

can activate AC and AR (NAM), reinforcing positive attitudes and subjective norms (TPB) by fostering awareness and a sense of accountability through informational cues and social interactions. The inclusion of PBC in TPB complements NAM by addressing the feasibility of actions and empowering users with actionable conservation tips. Methodologically, combining quantitative surveys to measure variables from both models and netnographic analysis of user-generated content enables an in-depth understanding of how social media facilitates norm activation and behavioural intention [24].

Studies support the relevance of these models: [14] highlight tourists' values in shaping personal norms for biodiversity protection, while [15] integrate environmental attitudes in an ecotourism model reflecting TPB's principles. Additionally, [24], [11], and [13] explore social media's impact on tourists' conservation attitudes, demonstrating the frameworks' adaptability. Integrating these insights offers a comprehensive methodology for examining social media's influence on conservation behaviour, notably through user-generated content (UGC).

5   Methodology

This study will adopt a mixed-methods research design (figure 1), combining netnographic analysis of social media content and survey research among international and national nature-based tourists visiting South Africa and using social media.

The quantitative data collection will involve a structured questionnaire measuring participants' awareness of environmental consequences, the ascription of responsibility, and the activation of pro-environmental personal norms. The questionnaire will include standardised items assessing various variables of interest, such as informational, normative, and emotional cues, alongside pro-environmental personal norms and behaviours. Participants will be selected using convenience and snowball sampling, with the survey administered electronically. The desired sample size would be 384, according to Krejcie and Morgan's guidelines (1970:607) when a population (N) of 72,000 is concerned. Data analysis will include descriptive statistics, exploratory factor analysis (EFA), correlation analysis, and regression analysis.

For qualitative data collection, the study will analyse publicly available Facebook data from tourism and conservation-related groups, focusing on South African travel communities from December 2024 to February

2025. Using tools like Netvizz, anonymous data from posts, comments, and interactions will be gathered, ensuring relevance through specific inclusion and exclusion criteria.

6   Future Research Directions

Future research directions for understanding the impact of social media on conservation behaviours among nature-based tourists can be explored through several avenues:

1. Longitudinal studies to track changes in social media engagement and pro-environmental norms over time.
2. Comparative studies to investigate variations in attitudes and behaviours between domestic and international tourists.
3. Expanding the qualitative aspect through interviews or focus groups to provide deeper insights into how social media shapes personal norms and motivations for pro-environmental behaviours.
4. Examining the effectiveness of various social media platforms, such as Instagram and Twitter, in promoting conservation awareness.
5. Exploring the role of influencers and user-generated content in driving conservation behaviours.
6. Investigating technological innovations like augmented and virtual reality to promote conservation messages.

Informing policy implications for using social media as a tool for environmental education and awareness campaigns in tourism.

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Virtual reality meets gastronomy tourism: the use of sensory-enabling technologies in tasting experiences

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Abstract. Given the importance of gastronomy for tourism and hospitality, this research explores the potential impact of immersive technologies on gastronomic experiences with local food products. Specifically, Virtual Reality (VR) offers new opportunities to create more engaging culinary experiences. This study addresses how VR can simulate environments that complement the food being tasted, thus affecting consumers' sensory experience and product evaluation. The congruency of the immersive environment on food perception is also considered. An experiment involving actual customers was conducted. Participants were randomly assigned to one of three conditions: a non-VR condition, a congruent VR environment, or a non-congruent VR environment, and were asked to sample a local product. In the VR-environment conditions, the participants had the VR experience while ingesting the product. After tasting the product, participants completed a questionnaire measuring the constructs of interest: arousal, pleasure, focused attention, processing fluency, and product evaluation. The results of this study aim to provide practical insights for tourism and hospitality professionals on how to integrate VR into gastronomic experiences in their aim to offer innovative, technology-enhanced culinary experiences.

Keywords: Tasting experience, Virtual Reality, Multisensory.

1 Introduction

Gastronomy is one of the key areas in the hospitality and tourism fields [1]. The role of food in tourism has gained attention in the last few years as tasting local food is recognized as a fundamental aspect of

tourism decision-making and overall experience [2]. As reported by [3], the global culinary tourism market reached a value of USD 11.5 billion in 2023, with an anticipated growth rate of 19.9% annually between 2024 and 2030, underscoring its significant potential within tourism. For destinations, offering local food is seen as a valuable asset that fosters deeper connections with local culture [4] while promoting the sustainable development of the community [5]. Thus, building innovative and authentic culinary experiences is essential in shaping tourists' perceptions and memories, making them a vital component of the overall travel experience.

Food experiences are inherently multisensory, including not only the flavors of the food but also the environment in which it is tasted. The atmosphere, design, and other related sensory cues shape the overall experience [6]. In recent years, the growing trend toward experiential dining has led consumers to seek unique, immersive experiences that go beyond traditional food service [7,8]. Therefore, tasting becomes an orchestrated event where the fusion of sensory inputs creates a memorable encounter [9].

Technological advancements are further enhancing this process. The emerging field of human-food interaction, a branch of human-computer interaction, specifically examines how technology can support and enrich food-related experiences [10]. Sensory-enabling technologies such as Virtual Reality (VR), offer innovative opportunities for exploring multisensory interactions across various contexts [11,12], including tourism-related tasting experiences. The application of VR in gastronomy tourism opens up new possibilities for enhancing tasting experiences by introducing sensory inputs that are otherwise difficult or impossible to achieve in traditional settings [13]. For instance, a virtual vineyard can enhance a wine tasting experience, virtually transporting consumers to the location where the grapes are grown, deepening their connection to the product and its origins. These immersive experiences have been shown to increase emotional engagement, ultimately promoting favorable behaviors [14,15].

VR is regarded as a valuable tool for creating food-related environments that elicit emotional responses from users [16]. VR holds potential for assessing consumer perceptions of local food, as it enhances engagement and involvement with products and brands [17]. Previous studies on VR and tasting experiences have focused on replicating real-world eating conditions [17,18] and examining visual-taste congruency

[19]. However, the existing literature remains in its early stages, with results that are often mixed or inconclusive. Based on the framework of [11], we consider tasting as the core experience, with VR generating empowered experiences that may either enhance (related empowered experiences) or divert (diverted empowered experiences) attention from the core. This work in progress aims to address how VR environments influence the taste of local food, specifically exploring how the congruency of the immersive environment (context of the experience) can modify the food tasting experience -enhancing it if congruent or diverting if non-congruent- and its subsequent effects on food perception. The results can provide destination managers with insights to offer more suitable and innovative tasting experiences.

2   Theoretical development

Devices with a high degree of technological embodiment, such as VR glasses, generate high levels of immersion and sensory stimulation in the experience [11]. Arousal refers to the feelings of excitement or stimulation that humans feel during an experience [20]. In the context of sensory-enabling technologies, VR can heighten arousal by stimulating multiple senses simultaneously [21]. These multisensory inputs, when aligned with the overall target experience (e.g., the food), are likely to trigger higher excitement states due to the immersive nature of VR. As noted in the congruity theory [22], individuals are inclined to seek cognitive harmony and consistency between various elements they encounter. Then, if the elements are congruent, users experience less cognitive dissonance, leading to stronger evaluations. In line with this theory, [23] note that congruent sensory cues are processed more efficiently, so it is proposed that viewing content related to the food will reinforce the effect of VR on arousal. Thus:

H1: *Tasting food in a VR environment (relative to non-VR) will positively affect consumers' arousal in the tasting experience.*
H2: *The effects proposed in H1 will be stronger when a congruent context is viewed in VR (compared to non-congruent VR and non-VR).*

Focused attention is the brain's capacity to direct and maintain concentration on a specific stimulus over a period of time [24]. Selective attention theory posits that individuals have a limited capacity for processing information and must selectively focus on certain stimuli while filtering out others [25]. When consumers experience heightened

arousal, such as excitement or stimulation, their cognitive resources are diverted toward managing the arousal itself. This state can reduce the individuals' capacity to focus on other sensory details. In a tasting experience, high levels of arousal may therefore reduce consumers' ability to focus on specific attributes of the product itself.

Nevertheless, arousal can amplify the pleasure consumers experience when tasting food by intensifying their emotional responses to the sensory experience. Arousal leads to pleasant and entertaining experiences in enjoyable situations [26]. Given the context of this research and the ability of VR technology to offer entertaining experiences [27], arousal is expected to have a positive impact on pleasure. Therefore:

H3a: *Perceived arousal will negatively affect consumers' attention in the food tasting.*

H3b: *Perceived arousal will positively affect consumers' pleasure in the tasting experience.*

Processing fluency refers to the subjective experience of how easily information is processed [28]. Perceived attention and pleasure positively influence consumers' fluency, as they enhance the ease with which sensory information is processed. If individuals pay attention to the cues in their environment, this ensures that sensory inputs are thoroughly processed, leading to more efficient cognitive responses [29]. When attention is directed toward relevant stimuli, the brain can integrate sensory information more efficiently, potentially facilitating a more fluent experience. Moreover, pleasurable stimuli are often processed with less cognitive effort and are more likely to elicit positive evaluations [30]. Together, it is proposed that higher levels of attention and pleasure will create a more fluent and effortless interaction with the food tasting experience:

H4: *Perceived attention in the food tasting (a) and pleasure (b) will positively affect consumers' fluency in the tasting experience.*

Following the processing fluency theory [31], when information about an object is easy to process (high fluency), it is more likely to be judged positively, whereas difficult processing (low fluency) can lead to negative evaluations. In a food tasting context, when the evaluation process is easier, consumers may be more likely to give favorable judgments because they face fewer mental obstacles and feel more confident in the evaluation. Therefore:

H5: *Fluency will positively affect consumers' evaluation of the product in the tasting experience.*

3   Methodology

To test the hypotheses, a one-factor between-subjects experiment was conducted. The experiment took place during three consecutive days at a central market, where actual consumers were recruited as participants in the study.

Once the participants arrived at the experimental room, which was located in the central market's basement, the research team provided them with a brief explanation of the study's procedures. Following this, participants were asked to sample a local food product (a type of cured sausage) and were randomly assigned to one of three conditions. In the control condition, the participants sampled the product with no VR complement. In the product-VR environment congruent experience, the participants tasted the product while watching a 360-degree video of a hike in the region where the experiment took place (the food product needs no cooking and is normally consumed in this kind of situation). In the product-VR environment non-congruent experience, the virtual hike was in a distant region from a different continent. Meta Quest 2 devices were used for the VR experiences. Thus, although the participants saw the product before tasting it, the intake was blind for them (as they were wearing the VR headset).

After tasting the product, participants completed the remaining sections of the questionnaire, including variables previously validated in the literature: three items for perceived arousal ([20]; e.g., "The tasting experience has been exciting"), three items for perceived attention ([32]; e.g., "I was totally focused on tasting the food"), three items for perceived pleasure ([20]; e.g., "The tasting experience has been pleasant"), two items for processing fluency ([33];e.g., "It has been easy to evaluate the product") and three items for the evaluation of the tasted product ([34]; "The product tasted is delicious"). The measurements were made on 7-point Likert scales, ranging from "1 = strongly disagree" to "7 = strongly agree". The final questions included control and sociodemographic variables. The final valid sample consisted of 139 participants. The research team is currently analyzing the data, which will be presented at the conference.

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Section 8: AI & Reservations

The Effect of Hotel Room Availability Display Methods on Consumer Purchasing Behavior During Online Reservations - Focusing on Dual Emotions

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Abstract. With the growth of Online Travel agencies (OTAs), online hotel reservations have surpassed offline bookings, making digital marketing strategies increasingly crucial for hotel sales. Since hotel rooms are perishable goods, effective online marketing is indispensable. This study, based on decision frame and framing effect theories in consumer psychology, investigates the impact of different methods of displaying room availability on consumer purchasing behavior. This experimental study adopts a 2 (Remain vs. Sold) x 2 (Rate vs. %) factorial design. Participants are randomly assigned to one of four groups and are exposed to different stimuli, after which they evaluate the stimuli using a 7-point Likert scale. These evaluations are used to analyze how combinations of the four numerical display methods influence consumers' perceived risk, impulsive behavior, and ultimate purchasing decisions. By exploring these effects, the study aims to provide insights into optimizing marketing strategies that leverage consumer psychology to increase bookings, thereby enhancing the effectiveness of hotel room sales across OTAs and other online platforms

Keywords: OTA, decision framework, framing effect, perceived risk, perceived impulsiveness

1   Introduction

The rise of Online Travel Agencies (OTAs) has revolutionized the tourism industry, providing travelers with the convenience of comparing and booking travel products on a single platform [4]. As of 2024, 82% of global bookings and 57% of hotel reservations are made online, with OTAs accounting for 41% of total travel market bookings [6, 19, 4]. OTAs offer 24/7 accessibility and price transparency, allowing consumers to make faster and more informed decisions [2]. Research indicates that price specificity (e.g., $159.99 vs. $160) and price framing

significantly influence consumer preferences and satisfaction [8]. The price framing effect is a powerful marketing tool that enables businesses to design pricing strategies that shape consumer perceptions and influence purchasing decisions. Consumers trust online platforms because of their clear price presentation and the ability to compare options, which drives hotel bookings through OTAs [22].

This study explores how the display of room availability ("Remain" vs. "Sold") and numerical formats ("Rate" vs. "%") impact consumer purchasing behavior, drawing on decision frame and framing effect theories [7, 21]. While previous research has examined pricing strategies such as discounts or color cues [10, 9], little attention has been given to how room availability displays affect consumer behavior. This study aims to fill this gap by investigating how these displays influence consumer choice, impulsiveness, and perceived risk during OTAs bookings.

The objective of this research is to provide strategic insights for OTAs and online platform providers, proposing effective methods for displaying room availability that positively influence consumer behavior and enhance hotel sales on OTAs platforms.

2   Literature Review

2.1   Decision Framework

The decision framework is a theoretical structure for analyzing factors involved in decision-making, such as information search, analytical techniques, and procedural control, which vary depending on the significance of the purchase [1]. Impulsivity plays a critical role in this process, as consumers often make different purchasing decisions based on how information is framed. On OTAs and online platforms, framing effects can be leveraged to influence consumer behavior. Specifically, positive (gain) frames highlight the benefits of rewards, thereby encouraging impulsive purchases, particularly in reward-driven scenarios. Conversely, negative (loss) frames trigger anxiety about missing out, further stimulating impulsive buying. The way information is framed—whether positively or negatively—has a substantial impact on consumer responses, particularly in emotionally charged decision-making contexts.

2.2 Framing Effect

The Framing Effect theory explains that consumer perception and reactions can change depending on how the same information is presented. For example, showing room availability as "90% available" might feel less urgent compared to "only 10 rooms left," which creates urgency and encourages faster decisions [22]. This effect also applies to price framing, where how pricing is shown influences purchasing decisions. In marketing and sales, how information such as price or product details is structured plays a crucial role in shaping consumer behavior and influencing their final decisions. This makes framing strategies key tools in promoting consumer engagement and sales.

2.3 Perceived Risk

Perceived risk refers to the uncertainty that consumers feel about potential negative outcomes in a purchasing situation. Different forms of risk, including financial, performance, and social risks, play a significant role in consumer behavior. Consumers experience heightened perceived risk in online shopping environments, which can be mitigated through trust-building and transparent information [14, 15].

2.4 Perceived Impulsiveness

Impulsiveness has long been an important topic in consumer behavior and marketing research. In the tourism and hospitality industry, impulsive purchases often occur due to emotional stimuli, time pressure, and perceived scarcity. Impulsiveness is also related to an individual's personality traits, with less self-controlled consumers more likely to react impulsively to external stimuli [9, 18].

3 Research Model and Hypotheses Development

This study builds on the decision framing effect proposed by Tversky and Kahneman (1981) and framing effect theory, which explain how consumer purchase perceptions and behaviors shift based on how information is presented [22, 21]. The research investigates how framing hotel room availability as positive ("Remain") or negative ("Sold") influences consumer decision-making, particularly in terms of perceived

risk and impulsiveness. Furthermore, the study compares the impact of numerical framing methods, such as "Rate" versus "%."

Participants will be exposed to various room availability displays through simulated scenarios and stimuli and will evaluate their purchasing perceptions and behaviors using a 7-point Likert scale. The objective of this research is to propose room availability framing as a strategic marketing tool for OTAs and online platforms.

This study extends prior research on decision framing in consumer contexts [22, 21]. The ultimate goal is to establish room availability framing as an effective marketing strategy.

The research model is presented in Figure 1. Hypotheses include:

Hypothesis 1: *Displaying room availability as "Remain" increases the likelihood of booking more than when displayed as "Sold."*

Hypothesis 2: *Perceived risk mediates the relationship between the room availability display method and booking likelihood. Specifically, when displayed as "Remain," perceived risk decreases, while displaying as "Sold" results in higher perceived risk.*

Hypothesis 3: *Perceived impulsiveness mediates the relationship between room availability display method and booking likelihood. When displayed as "Remain," perceived impulsiveness increases, while "Sold" results in lower perceived impulsiveness.*

Hypothesis 4: *The numerical display method moderates the relationship between room availability display method and booking likelihood. When the number is displayed as a "Rate", perceived risk decreases, increasing booking likelihood.*

Hypothesis 5: *When the number is displayed as a "Rate", perceived impulsiveness increases, thereby increasing booking likelihood.*

Hypothesis 6: *When the number is displayed as a "%", the room availability display method has no significant impact on booking likelihood.*
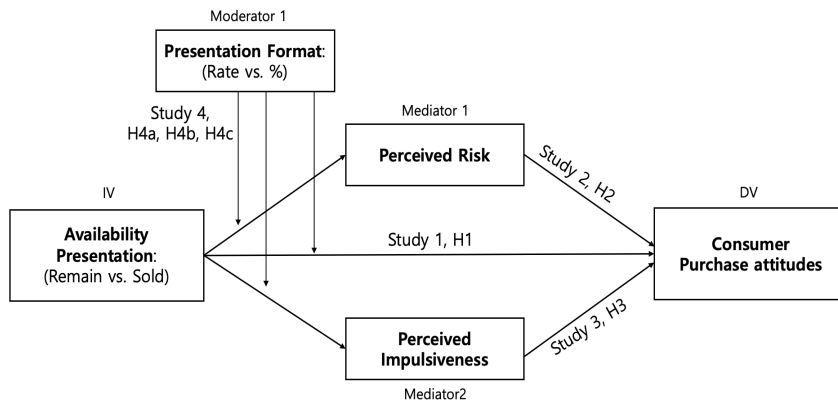
Fig. 16. Research Model

4   Research Methodology

This study employs a 2x2 experimental design to investigate how room availability displays ("Remain" vs. "Sold") and numerical presentation formats ("Rate" vs. "%") influence consumer purchase decision-making.

Using a between-subjects design, participants are randomly assigned to one of four groups. They are exposed to stimuli featuring various room availability displays within scenarios that simulate an actual OTAs booking process. After viewing the stimuli, participants evaluate the psychological impact of the presented information using a 7-point Likert scale, measuring perceived risk and impulsiveness.

The objective of this study is to analyze how these factors affect consumer purchasing behavior in the context of online hotel reservations. The stimuli are presented in Figure 2.
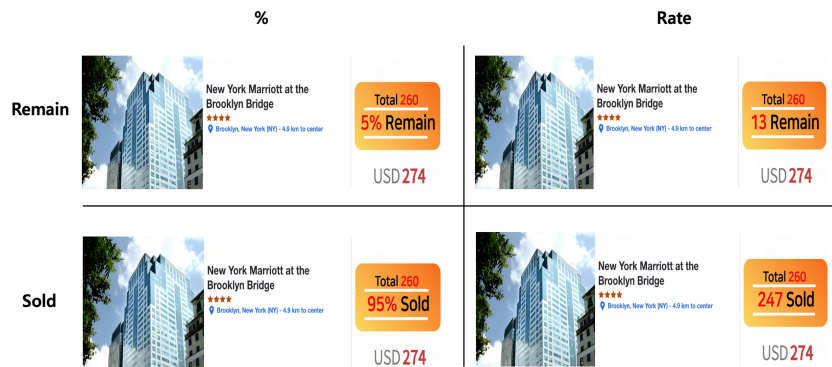
Fig. 2. Stimuli

5   Conclusion

This study investigates how the presentation of hotel room availability ("Remain" vs. "Sold") and numerical formats ("Rate" vs. "%") influence consumer purchasing behavior in online bookings. Grounded in decision-making and framing effect theories [7, 21], the research aims to strengthen marketing strategies for online reservation platforms.

The study examines how these formats affect perceived risk (e.g., fear of rooms selling out) [3, 5, 14] and impulsiveness (e.g., urgency to book quickly) and how these perceptions are associated with actual purchasing behavior.

The primary objective of this study is to validate these effects through future experimental research, with the aim of optimizing sales strategies on OTAs and other online booking platforms. While this study focuses on hotel rooms, the findings are expected to be applicable to other industries utilizing online booking platforms, such as airlines, travel agencies, restaurants, and product sales.

Future research could further explore factors such as quality levels, brand loyalty, lead time, and the extent of product information exposure to develop more specific and effective marketing strategies.

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AI Pricing Tools in Online Travel Agents: Spatial Context of Platform Capitalism

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Abstract. The advancement of Artificial Intelligence (AI) and big data analytics has become a widely discussed global issue, with AI notably reshaping various aspects of daily life, including revenue management (RM) in the lodging industry. This transformation raises potential risks, particularly for smaller enterprises, local communities in less developed destinations, and environmental sustainability. As a result, it is crucial to critically assess the impact of AI on RM in the hotel sector.

This study aims to identify segments of the lodging market influenced by platform capitalism, focusing on RM within lodging services. The empirical objective is to examine site-specific and situational factors influencing variability in hoteliers' willingness to adopt dynamic pricing methods offered by Online Travel Agents, powered by AI solutions. The analysis centres on hotels, motels, and guesthouses operating in Poland in 2024. To achieve this, the Random Forest Classifier is employed, enabling the identification of feature-based and spatial patterns in the adoption of AI-driven revenue management tools.

The findings suggest that the most popular hotels, located in metropolitan areas, offering higher-priced services and demonstrating greater awareness and knowledge of revenue management, are most likely to adopt AI-driven dynamic pricing methods provided by intermediaries.

This study's practical contribution is offering a more nuanced perspective on the current enthusiasm surrounding AI in hotel RM. By highlighting the control exerted by platform capitalism over tourism destinations and lodging entities, this research aims to inform RM practitioners, destination managers, educators, and researchers about the broader consequences of AI application in the industry.

Keywords: Artificial Intelligence, Revenue Management, Dynamic Pricing, Platform Capitalism, Online Travel Agents, Geographical Volatility, Poland.

1   Introduction

Dynamic pricing is one of the integral concepts and an essential part of revenue management (RM) regarding pricing strategies (Ivanov, 2014; Ivanov & Piddubna, 2016). The emergence of big data reshapes how information is processed across all industries. Also, using data for pricing strategies transformed RM practices (Talón-Ballestero et al., 2022). Integrating artificial intelligence (AI) into creative and operational processes fundamentally transforms industries, including tourism and hospitality. AI tools like machine learning algorithms, data analysis platforms, and predictive models are increasingly utilized in marketing, customer experience, and operational efficiency (Doborjeh et al., 2022). In lodging RM, AI and big data analytics play a crucial role, particularly in the adoption of dynamic pricing strategies facilitated by Online Travel Agents (OTAs). While evolving technologies offer significant operational efficiencies, they also pose potential risks for smaller enterprises and local communities in underdeveloped tourism destinations, as they may create dependencies on OTAs – the large multinational companies that have access to the raw resource – data – as well as the knowledge, skills, and technology that enable its use, often referred to as 'platform capitalism.' (Srnicek, 2016). For the consumer purchasing process, OTAs are the most popular distribution channels for hotel rooms (Abrate et al., 2019).

This study investigates the factors driving geographical variations in hoteliers' willingness to adopt dynamic pricing methods powered by AI through OTAs, focusing on such transformations' environmental and socio-economic consequences. The study is guided by an empirical exploration of Booking.com's Genius marketing programme and the application of machine learning techniques to understand critical features influencing hoteliers' decisions.

2   Literature Review

Customers often have certain expectations about the price they pay for a product or service (Kotler & Armstrong, 2014). They evaluate prices by comparing them to the most recent price or referring to what others say they have paid for a similar offer (Sahut et al., 2016). This price expectation and actual price presentation are crucial in their choice process (Viglia et al., 2016). Technological tools, including AI, have made

it easier for companies to apply pricing strategies such as dynamic pricing (Abrate et al., 2019). Dynamic pricing covers integrated strategies designed to sell a restricted amount of perishable inventory to the most lucrative combination of consumers, optimizing profitability (Alderighi et al., 2022).

RM is an essential instrument within the marketing management realm for matching supply and demand through applications of information systems and pricing strategies to deliver the right product to the right customer at the right time through the right channel and the right price (Ivanov & Zhechev, 2012; Viglia & Abrate, 2020). The development of the Internet, social media, websites, smartphones, smart applications, and the overall virtual world changed how information is distributed and how people plan and consume (Buhalis et al., 2022; Buhalis & Law, 2008; Dwivedi et al., 2023). Personalisation, known as one-to-one marketing (Arora et al., 2008), is a specialized form of product and service differentiation and is an essential element of customer experience (Ozturk et al., 2017). Creating personalized and memorable customer experiences (also the thought process of purchasing) has always been at the heart of the service industry (Oyner & Korelina, 2016). The extensive use of dynamic pricing with personalized recommendations also greatly influences how customers search and book hotel rooms and the strategy implementation level varies from hotel to hotel (Alderighi et al., 2022).

However, this ongoing technological transformation has implications that pose potential threats, particularly for less privileged enterprises, local communities in underdeveloped destinations, and the environment. Hence, post-capitalist vision of fair pricing is discussed (Napierała & Pawlicz, 2023). RM applications, including AI-driven ones, must consider not only the interests of hotel owners and managers, but also those of employees, suppliers, local communities in the places where hotels are located, their representatives and authorities, as well as Nature, whose resources are fundamental to tourism attractiveness and quality of life in a broader context. Consequently, the impact of AI development on RM in the hotel industry warrants careful examination.

3   Methodological Framework

This study aims to identify the geographical and market-specific factors that influence hoteliers' willingness to adopt AI-powered dynamic pricing methods offered by OTAs. Specifically, the study focuses on Booking.com's Genius programme, which uses machine learning to suggest optimal pricing strategies based on various variables.

Data is collected from Booking.com using Octoparse, a web-scraping application, to extract information on lodging entities. The dataset includes site features such as price, star rating (ranging from 1 to 5, with non-rated hotels classified as 0), overall customer rating (from 1 to 10), and whether the lodging entity is part of a hotel chain. Situational factors such as distance from the regional centre and local population density are also considered.

A Random Forest Classifier is applied to the dataset to identify the features that most significantly influence a lodging entity's willingness to delegate RM control to AI tools like the Genius programme. The Random Forest Classifier, a tree-based classifier (Pal, 2005), is well-suited for this analysis due to its robustness in handling complex, non-linear relationships between variables. To assess the spatial variance in the adoption of dynamic pricing models, spatial patterns in the adoption of AI-driven RM tools are identified based on cartographic analysis of nodes of aforementioned tree-based classification. This spatial analysis is crucial for understanding how local economic conditions, market dynamics, and platform capitalism influence decision-making in the hospitality sector.

4   Initial Results and Limitations

After web scraping Booking.com and curating the data (including the removal of duplicates and the imputation of missing values), 3,797 hotels, motels, and guesthouses operating in Poland and selling their accommodation services on 24 August 2024 for check-in on 16 October 2024 were identified. Of these, 2,177 were included in the training set to run the Random Forest Classifier.

The main limitation of this research is its reliance on a single data source: Booking.com. It has been confirmed that independent hotels are overrepresented on the platform. Furthermore, large and high-category

hotels offer only a limited portion of their inventory through intermediary channels such as Booking.com (Martin-Fuentes & Mellinas, 2018). The findings suggest that the most popular hotels – located in metropolitan areas, offering higher-priced services, and demonstrating greater awareness and knowledge of revenue management – are the most likely to adopt AI-driven dynamic pricing methods provided by intermediaries. Interestingly, hotels located within a 100 km radius of metropolitan centres, which sell their rooms at the lowest rates, were unable to adopt AI-driven technology to support revenue management decisions. The cheapest services, even when offered by hotels in central locations, are outside the interest of platform capitalism. We confirm that AI-driven technology primarily targets revenue-focused entities.

5 Conclusion and Future Research Directions

The added value of this study lies in its contributions to theory and practical applications in RM. Academically, it advances understanding of how AI and machine learning tools used by OTAs influence hoteliers' adoption of dynamic pricing models. Using techniques like Random Forest Classifier followed by the cartographic analysis offers a novel approach to analysing geographic and market-specific factors shaping AI adoption, contributing to the literature on platform capitalism in tourism.

Practically, the study provides insights for industry stakeholders, highlighting the impact of AI-driven RM on smaller businesses and less developed destinations. It raises awareness of potential risks associated with platform dependency while showcasing AI's potential to improve pricing and efficiency.

Future research could explore the long-term effects of AI-based dynamic pricing on customer satisfaction and behaviour, comparing these models with traditional approaches. Further investigation into the ethical implications, such as transparency and fairness in AI algorithms, is also needed. Finally, future research could explore the environmental implications of AI-driven pricing strategies. Do these technologies encourage overconsumption and increased resource use in high-demand tourism areas, or social exclusion affecting tourists for whom the price is no longer affordable, or can AI be leveraged to promote more sustainable tourism practices?

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Decoding AI in Travel Planning: a comparative semiotics and statistical study

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Abstract. This study explores the interactions between humans and Gemini, Google's conversational AI, during travel planning conversations. Focusing on 54 interactions, this research combines semiotic analysis and statistical text analysis to uncover how users from diverse cultural backgrounds engage with AI. Semiotics analysis, performed using Atlas.ti, identified key travel-related signs and cultural meanings, while ChatGPT facilitated statistical analysis, revealing patterns in word frequency and topic distribution. By applying Jaccard Similarity, along with Precision, Recall, and F1 Score, the study evaluates the concordance between the analyses conducted by ChatGPT and Atlas.ti, achieving a moderate agreement with a Jaccard index of 0.67. The findings highlight the complementary strengths of qualitative and quantitative tools for understanding AI-mediated interactions, providing insights into how AI systems can enhance personalized travel planning across cultural boundaries..

Keywords: Human-AI Interaction, Semiotic Analysis, Statistical Text Analysis, Travel Planning AI.

1   Introduction

Generative AI (GAI) has transformed decision-making processes across industries, particularly in travel planning. AI-driven systems like ChatGPT and Gemini leverage natural language processing (NLP) to deliver real-time, personalized recommendations, enhancing user experiences in tourism and hospitality. However, gaps remain in understanding how individuals from diverse cultural backgrounds interact with these systems, particularly in the context of symbol interpretation and decision-making.

   This study addresses this gap by examining 54 conversations where users from different nationalities planned trips to Paris using Gemini. The research combines semiotics analysis—to interpret cultural and

symbolic meanings—and statistical text analysis—to quantify conversation patterns. Semiotics analysis identifies how users interpret signs and cultural codes, while statistical analysis explores word frequency, sentiment, and topic distribution. By comparing the outputs of Atlas.ti and ChatGPT, the study investigates the strengths and limitations of these tools in analyzing AI-mediated interactions.

The theoretical framework integrates concepts from Generative AI in travel decision-making, Human-Computer Interaction (HCI), and Media Richness Theory (MRT). These theories collectively inform how generative AI systems facilitate user interaction, decision-making, and personalized travel planning experiences. This context establishes the foundation for the methodological approach and comparative analysis.

2   Theoretical Background

2.1   Generative AI in travel decision-making

Generative AI offers real-time recommendations and assistance throughout the travel experience (Wong et al., 2023). Systems like ChatGPT and Gemini use NLP to deliver contextually relevant advice, enhancing user interactions (Singh et al., 2023). Despite these benefits, trust in GAI is influenced by user experience and concerns over AI errors, leading to varying degrees of reliance on AI-generated recommendations (Kim et al., 2023; Christensen et al., 2024).

2.2   Human-Computer Interaction (HCI) theory

HCI theory explores how users engage with technology, emphasizing usability, cognitive load, and emotional responses (Cheung & Dall'Asta, 2024). In travel planning, HCI explains how AI systems like ChatGPT interpret user inputs and offer personalized recommendations, enhancing interaction through AI-mediated communication.

2.3   Media Richness theory (MR)

MR theory posits that richer communication media are more effective for reducing uncertainty in decision-making (Daft & Lengel, 1984). In travel planning, conversational AI serves as a rich medium, providing timely, customized solutions that enable confident decision-making.

3   Methodology

This study analyzes 54 conversations with Gemini, where users from diverse nationalities such as Mexico, Spain, the United States, China, the Dominican Republic, Argentina, and France planned trips to Paris. The conversations were prompted uniformly, but users interacted autonomously, allowing for cultural variations. Participants were selected through a purposive sampling method to ensure cultural diversity. The socio-demographic profiles include individuals from Europe, Latin America, and Asia, with an equal gender distribution and varying age ranges (18-45 years). This diversity provides a robust basis for examining cultural nuances in AI interactions.

A combination of semiotics analysis (qualitative) and statistical text analysis (quantitative) was employed, using ChatGPT and Atlas.ti (version 23.2.1), where its AI capabilities were not utilized, due to the focus on manual coding for richer interpretative depth. The semiotic analysis aimed to identify cultural and symbolic meanings in the conversations by identifying key travel-related signs, such as landmarks (Eiffel-Tower) and accommodations, examining both the literal meanings (denotation) and cultural associations (connotation) of the sign, analyzing the relationship between signs within the conversation, and identifying cultural codes shaped by the participants' nationalities.

The statistical analysis involved quantifying conversation patterns through the following steps:Text processing: Data was cleaned and standardized.

1. Exploratory frequency analysis: Word frequency and TF-IDF were used to identify key terms, such as "hotel" and "landmark."
2. Sentiment analysis: Sentiment polarity was assessed to determine the emotional tone.
3. Topic analysis: Latent Dirichlet Allocation (LDA) was used to identify key themes, such as accommodations and gastronomy.
4. Semantic network analysis: Word co-occurrence techniques were used to reveal relationships between important terms.

Finally, to evaluate the agreement between ChatGPT and Atlas.ti, Jaccard Similarity and Precision, Recall, and F1 Score were applied to measure overlap in codes or themes between the two systems through the Jaccard method, where A and B represent the sets of codes from ChatGPT and Atlas.ti.:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

And, to establish how well ChatGPT matched Atlas.ti's relevant codes through the Precision method, while Recall measured the proportion of Atlas.ti's codes captured by ChatGPT, and the F1 Score provided a balanced evaluation of both (Yacouby & Axman, 2020).

4   Preliminary Results

The analysis provided key insights into how individuals from diverse cultural backgrounds interact with Gemini when planning travel. The main results obtained by semiotics analysis revealed that:

- Common signs: Landmarks, accommodations, and gastronomy were consistently referenced across all nationalities.
- Connotations: While landmarks like the Eiffel Tower held similar denotations, connotations varied. Spanish and Mexican users emphasized history, while Chinese users focused on modernity and global prestige.
- Syntax and relationships: Conversations often linked landmarks and gastronomy, integrating sightseeing with dining.
- Cultural codes: Cultural codes revealed different planning approaches based on nationality, with Latin American participants emphasizing social experiences and Europeans focusing on historical aspects.

The statistical analysis provided the following insights:

- Word frequency: Terms like "hotel," "budget," and "Eiffel Tower" were most frequently mentioned.
- Sentiment analysis: Positive sentiment was expressed when discussing landmarks and food, while budget-related topics elicited negative sentiment.
- Topic analysis: Dominant topics included accommodations, landmarks, and gastronomy, with budget concerns frequently intersecting these discussions.

Regarding the concordance results, the Jaccard Similarity index of 0.67 indicated moderate agreement between ChatGPT and Atlas.ti.

- Precision was 75%, showing that ChatGPT matched most of Atlas.ti's themes.
- Recall was 86%, with ChatGPT capturing the majority of themes coded by Atlas.ti.
- The F1 Score was 80%, reflecting high concordance between the two systems.

The analysis of human-AI conversations using both Atlas.ti and ChatGPT reveals a strong concordance between the two systems, especially in identifying the most culturally significant and experiential aspects of travel planning conversations. Both tools excel in capturing topics related to landmarks, gastronomy, and cultural codes, which are crucial for understanding the underlying structure of these interactions. Landmarks such as the Eiffel Tower and gastronomy discussions about French cuisine were prominent across conversations, reflecting the importance of these symbols in planning a trip to Paris. This alignment indicates that both systems are capable of recognizing key themes, despite their differences in approach. The focus on cultural codes is particularly important in understanding how diverse nationalities interpret these aspects of Parisian culture. For example, participants from Latin America highlighted social experiences, while European participants emphasized historical and architectural significance. Both systems successfully captured these cultural nuances, reinforcing their ability to analyze and categorize critical conversational elements.

However, the two systems also display unique strengths that could make them valuable complementary tools. Atlas.ti, a qualitative analysis software, excels in structured sentiment analysis and in identifying deeper cultural nuances embedded in conversations. It enables researchers to delve into the emotional responses and symbolic meanings attached to various travel-related signs, offering a richer understanding of the user's feelings toward specific aspects of their trip. For example, while ChatGPT can identify the practical elements of accommodation or budget, Atlas.ti can assess whether users expressed positive or negative emotions toward particular suggestions or experiences. This capacity for emotional and symbolic analysis is essential for understanding how users engage with AI systems on a deeper, more subjective level.

On the other hand, ChatGPT offers broader practical insights, particularly when it comes to accommodations and the statistical highlights of the conversations. ChatGPT's ability to perform TF-IDF analysis allows it to pinpoint the most relevant terms in each conversation, providing valuable information about what users prioritize when planning their trips. It efficiently identifies common concerns, such as finding affordable accommodation in central locations, and offers insights into the structure of the conversation, revealing patterns and key topics across the dataset. This statistical strength makes ChatGPT highly effective in generating practical insights that can be applied to a wide range of user needs.

Given the unique strengths of both tools, there is significant potential for complementarity between them. While Atlas.ti excels in qualitative and emotional analysis, ChatGPT provides robust quantitative insights and practical recommendations. For instance, combining Atlas.ti's sentiment analysis with ChatGPT's ability to analyze accommodations could offer a more comprehensive view of the user's travel preferences. Atlas.ti's ability to uncover cultural nuances and emotional responses could enrich ChatGPT's practical insights, providing a fuller picture of what users want and how they feel about different travel options. Together, these tools could offer a holistic approach to understanding human-AI conversations, addressing both the qualitative depth and quantitative breadth of these interactions. This potential for complementarity suggests that future research could explore the integration of these tools, leveraging their respective strengths to offer richer, more meaningful insights into how travelers plan their trips using AI systems.

5   Discussion and future research directions

The study revealed significant insights into how people from different cultural backgrounds interact with AI. The analysis showed how individuals from various nationalities interpret travel-related signs, with Atlas.ti identifying subtle cultural nuances. ChatGPT, on the other hand, provided structured insights into word frequency and sentiment.

Both systems showed strong agreement, as seen in the Jaccard Similarity and Precision, Recall, and F1 Score metrics. This indicates that while ChatGPT and Atlas.ti have different approaches, combining them creates a powerful tool for analyzing human-AI conversations.

5.1 Limitations

The study's dataset of 54 conversations limits the generalizability of findings. Additionally, selection bias may arise from the purposive sampling method. Future research should include larger, more diverse datasets and explore other AI models like Copilot. Finally, while Atlas.ti's AI capabilities were not utilized, their integration could enhance future analyses.

5.2 Future research directions

In the future, research should focus on how AI systems can learn from previous interactions to provide more personalized suggestions. Expanding the scope to include other travel destinations would offer broader insights into the role of AI in decision-making across different cultures. Furthermore, developing hybrid systems that integrate ChatGPT and Atlas.ti methodologies could further enhance AI-mediated conversations.

6   Conclusions

This study shows how ChatGPT and Atlas.ti can work together to analyze human-AI conversations effectively. The analysis uncovered cultural nuances and key patterns in travel planning. The high Jaccard Similarity and F1 Score between the two systems confirm the value of using both qualitative and quantitative approaches in AI-mediated decision-making.

The research provides insight into how generative AI systems like Gemini can improve personalized travel planning. Future studies should explore larger datasets and examine the ethical considerations of AI-mediated decision-making.

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Instrument Development for Analysing Daily Deals Websites Adoption in Hospitality: Insights from the TOE Framework

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Abstract. This paper examines the adoption of daily deal (DD) websites in the hospitality industry using the Technology-Organisation-Environment (TOE) framework as the primary theoretical foundation. The study combines a literature review with qualitative interviews conducted with Croatian hotel managers responsible for sales, revenue management, and marketing to identify the key technological, organisational and environmental factors that influence the decision to adopt DD platforms. The TOE framework provides a structured approach to understanding these influences and focuses on aspects such as relative advantage, complexity, organisational readiness and competitive pressures. Insights from hotel managers revealed operational benefits, including increased off-season occupancy, alongside concerns about potential long-term impacts on brand perception and customer loyalty. By providing a comprehensive understanding of DD adoption, the study offers practical implications for hotel managers in strategically incorporating DD platforms into their distribution strategies, ultimately enhancing competitiveness and operational efficiency. **Keywords:** TOE framework, daily deals websites, hospitality industry, instrument development, managers' perspective

1   Introduction

The rise of e-commerce and online shopping has revolutionised the way tourists choose their hotels and buy travel. As a result, e-distribution is increasingly becoming an essential element of hotel distribution (Law, Buhalis, & Cobanoglu, 2014; Jiang, 2014) and an essential aspect of strategic hotel marketing activities (Meriläinen, 2017). One of the innovative third-party mediated marketing strategies that hotels have adopted after the 2008 global financial crisis is the use of daily deal

websites (DDs), also known as flash sales, group buying or private sale websites (Geerts & Masset, 2022; Gupta & Keiningham, 2012). These time-sensitive promotions offer significant discounts to customers who book within a certain period, create a sense of urgency, encourage impulse purchases and help hotels fill unsold inventory in the low season (Yi, 2023). The COVID-19 pandemic brought unprecedented disruption to the hospitality industry, leading to widespread closures, lower demand and changes in consumer behaviour. Hotels increasingly relied on digital distribution channels, including DD platforms, to boost demand and recover occupancy after the lockdowns. In addition, the ongoing cost of living crisis has increased consumer price sensitivity, further emphasising the relevance of DDs as a strategic tool to attract price-conscious travellers.

Overtime DDs become an important Internet Distribution System (IDS), similar to online travel agencies (OTAs), and part of the hotels' wider distribution portfolio (Budler et al., 2020; Minor, 2017). However, despite their widespread use in the industry, little research has been conducted into the decision-making processes behind the use of DDs. Previous studies, such as Piccoli & Dev (2014), Berezina & Semrad (2015), Minor (2017), primarily investigated broader motivations behind the adoption of DDs, but these studies were conducted prior to the COVID-19 pandemic and the more recent cost of living crisis. This shift in economic conditions emphasises the need for new insights into how these channels fit into today's hospitality ecosystem. Furthermore, while existing studies have predominantly relied on qualitative approaches, there remains an opportunity for more quantitative research to empirically examine the factors influencing DD adoption among hotel managers.

Therefore, this study aims to answer the following questions:

1. What are the main technological, organisational and environmental factors influencing the adoption of DDs in the hospitality industry?
2. How do hotel managers perceive the impact of DDs on their operational and marketing strategies?
3. What insights can be gained from the qualitative interviews to support the development of a questionnaire to further analyse the adoption of DDs in the hospitality industry?

Research shows that DD platforms can increase operational tasks, attract demanding discount customers and cause communication problems due to the potential negative impact on a hotel's image (Minor & Bratec, 2020). This study fills a gap in the literature by focusing on the adoption of DD platforms in the context of the COVID-19 pandemic and the economic challenges that followed. This research aims to develop a robust conceptual model based on the TOE framework that provides a basis for quantitatively analysing the key factors influencing hotel managers' adoption of DD.

2　Theoretical background

The Technology Acceptance Model (TAM) has been widely used in tourism research to investigate the acceptance of technology (Pourfakhimi et al., 2019). However, many scholars, such as El Archi and Benbba (2023), argue that the narrow focus of TAM on individual behaviour limits its applicability in complex, organisational settings such as hotels adopting DDs. Similarly, while the Unified Theory of Acceptance and Use of Technology (UTAUT) provides insight into user intentions (Venkatesh et al., 2003), it does not take into account external pressures or organisational readiness, both of which are critical for evaluating the adoption of e-distribution platforms in the hospitality industry.

Given these limitations, the TOE framework (Tornatzky & Fleischer, 1990) offers a more comprehensive approach, especially for understanding the adoption of DDs in hotels. TOE considers not only technological factors, but also the organisational capabilities and external pressures that influence decision-making (Wang et al., 2016). This makes TOE particularly relevant for understanding the adoption of DD platforms in dynamic and competitive sectors such as hospitality. Building on empirical evidence, this study applies the TOE framework to examine the key factors influencing the adoption of DDs in the hospitality industry.

Technological context
Several key technological factors influence the adoption of DDs, including relative advantage, compatibility, complexity and perceived cost. Hotels are using DDs to increase their market presence, fill empty

capacity and thus increase their profitability. However, the compatibility of these platforms with existing business practises and booking systems is crucial for seamless integration (Nguyen & Vu, 2022). In addition, the complexity of using and managing DDs, which may require specialised knowledge, can be a major challenge (Pizam et al., 2022). Finally, concerns about the perceived costs of implementing and managing offers on DD platforms, including staff training and ongoing support, may also hinder their adoption (Premkumar & Roberts, 1999).

Organisational context
The adoption of DD websites in hotels is strongly influenced by various organisational factors, including top management support, organisational readiness and company size. Top management support is essential for the successful adoption of DDs, especially when leadership is motivated by the potential for competitive advantage and is aware of the benefits (Pizam et al., 2022). Organisational readiness refers to the availability of financial, technical and human resources required to adopt DDs, with hotels needing both sufficient resources and skilled staff (Abed, 2020; Pizam et al., 2022). Finally, the size of the organisation also plays a role, as larger hotels with more capital, revenue and staff are generally better equipped to implement DD platforms (Wang et al., 2016), despite the smaller organisations finding DDs particularly useful (Minor, 2017).

Environmental context
The environmental context emphasises external factors that influence a hotel's decision to introduce DD websites. Key factors include competitive pressure, perceived trend, consumer pressure and external support. Competitive pressure plays an important role in persuading hotels to adopt DD platforms (Pizam et al., 2022; Premkumar & Roberts, 1999). The perceived trend in the hospitality industry also influences adoption. The more hotels use DD platforms, the greater the pressure to follow this trend in order to stay relevant and keep up with industry standards (Nguyen & Vu, 2022). Consumer pressure continues to drive the adoption of DD platforms, as a significant proportion of hotel customers prefer to use DD platforms to book accommodation (Wang et al., 2016; Leung et al., 2015). Finally, external support is crucial for the adoption of DDs. Hotels can rely on technical support, training and resources

provided by third-party providers and DD platforms themselves to ensure effective implementation and utilisation of these systems (Premkumar & Roberts, 1999).

3   Methodology

The research began with a literature review on DD adoption, which led to the selection of the TOE framework due to its flexibility and scope. A pilot interview and ten semi-structured interviews with Croatian hotel managers responsible for sales, revenue and marketing were conducted to refine the research questions and develop the questionnaire. Croatian hotels, which are highly dependent on seasonal demand, provided a relevant context for this study, although the results may have limited transferability to other regions. The interviews, which lasted 30–60 minutes, were conducted online, recorded, transcribed and analysed using NVivo and Braun & Clarke's (2006) thematic analysis. The themes from the interviews and the findings from the literature shaped the variables within the TOE framework.

4   Preliminary results

Interviews with hotel managers confirmed some expected findings, such as operational challenges due to increased administrative tasks and short-term benefits such as improved occupancy. However, most managers praised the good relationship with DDs, particularly emphasised their quick communication and intention to continue the cooperation. Larger hotels in particular, with their greater financial and technical resources, were more confidence in adopting DDs, while smaller hotels expressed concerns about limited resources and the risk of over-reliance on discount channels. While competitive pressures were expected to be the driving force behind the adoption of DDs, some managers were unexpectedly concerned about how DDs could negatively impact their brand image, particularly in the post-pandemic market. Larger hotels also showed more experience in differentiating their offerings in different markets, utilising local, global and niche DD websites, while smaller hotels worked primarily with local DDs in times of lower occupancy. These results offer new insights into the different strategies used by different hotel sizes and how they deal with the challenges of DDs compared to previous studies.

Based on the TOE framework, a conceptual model was developed to illustrate the interaction between these factors and their influence on the intention to adopt DDs.
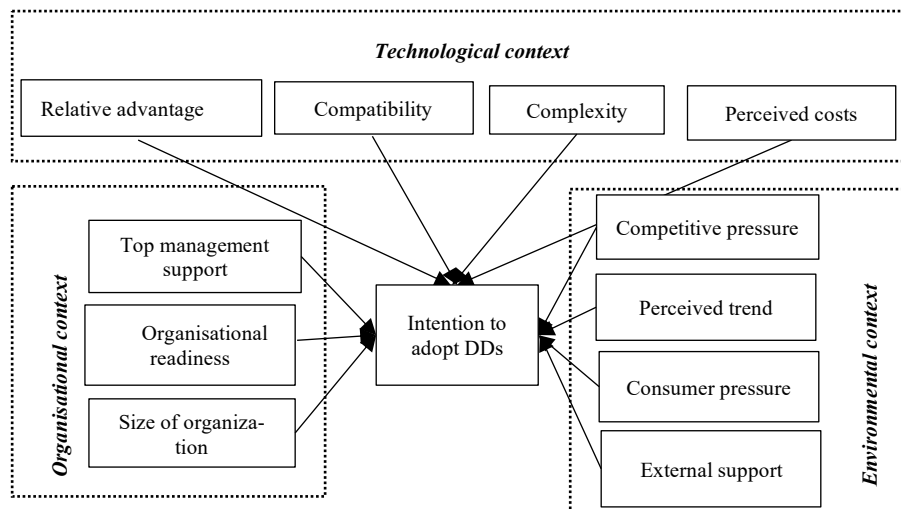

Fig. 1. Conceptual model

The model shows how technological, organisational, and environmental factors influence adoption decisions, forming the basis for forthcoming quantitative analysis of DD adoption.

1 Conclusion

This working study provides a theoretical and practical framework for understanding DD adoption in the hospitality industry using the TOE framework. It identifies key factors influencing the adoption process and develops a questionnaire as a basis for further quantitative research. The findings highlight the importance of aligning DD adoption with organisational resources and strategies, and provide practical guidance for managers to overcome challenges such as operational pressures and brand impact. The developed questionnaire provides a solid foundation for future quantitative research, which the authors began conducting in autumn 2024. Future research could test the model in different geographical contexts or with different types of hotels to improve its generalisability and explore the long-term impact on performance and brand perception.

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SECTION 9: AR/VR/Metaverse

Effects of augmented reality visitor guides under consideration of nudging and visual design

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Abstract. Tourist experiences no longer only take place in the real world, but are expanded to include digital components or virtual worlds. AR applications on smartphones or handheld devices are particularly suitable for traveling, as they are a constant and familiar companion when on trips. Tourism providers or destination management companies could use AR applications for visitor management and to regulate visitor flows. Visual nudges might increase the steering effect of AR applications. This paper investigates the influence of visual and content design of an AR guide on tourist behavior. A study including an experiment with two sub-groups (n=115) focused on an AB test of an exemplary AR guide mock-up for route recommendations. Results show that nudging via AR might have positive effects on increasing the attractiveness of lesser-known destinations, and thus, on balancing visitors. Limitations of the paper are due to the small data set and the fact that no real behavior but intentions of visitors were evaluated.

Keywords: Augmented reality, nudging, visitor management.

1   Introduction

Tourist experiences such as city breaks, beach vacations or day trips no longer only take place in the real world, but are expanded to include digital components or virtual worlds [5]. One possible extension is the technology of augmented reality (AR), in which digital or virtual objects are overlaid on the user's real field of vision. Azuma [2] defines AR as a variation of Virtual Environments that completely immerse a user inside a synthetic environment. He emphasizes that AR allows the user to see the real world, with virtual objects superimposed upon or composited with the real world as a supplement reality. Aichner et al. [1] add that AR enables the merging of real and virtual objects as well as interactive experiences in 3D and in real-time.

AR applications on smartphones or handheld devices are particularly suitable for tourist experiences [5], as they are a constant and familiar companion when traveling. For example, exhibits in the natural history museum such as whale or dinosaur skeletons can be overlaid by AR in the museum app and the entire, realistic body of the animals can be displayed. AR applications are also already widespread in cultural tourism, with national and international examples showing the use of AR to reconstruct historical buildings and cultural heritage sites, in museums and exhibitions, to enhance historical sites or to increase the attractiveness of less frequented spots [6, 10].

AR applications also allow tourism providers to collect data during app use, e. g. tourist numbers, locations or mobility patterns [9]. This enables tourism providers to use AR applications for their visitor management. For example, urban destinations can guide visitors with signage, city maps or apps with various route suggestions in order to regulate visitor flows. This might be necessary due to overcrowding or to generate more value. This provision of information is referred to as nudging or sorting [3]. Here, visual nudges [15] might increase the steering effect of AR applications.

Against this background, it is important to analyze possible synergies of AR applications in tourism and visitor management. In particular, the potential of AR as a nudging instrument for influencing tourist behavior should be considered. Therefore, the following research question is derived:

> *RQ: What influence does the visual and content design of an AR guide have on the recommendation assumption of the alternatives or nudges on the visitors?*

2 Theory

In the context of visitor management, visitor guidance is currently of central importance following the return of tourism demand to pre-covid times. Spatially and temporally effective unbundling and steering strategies should be used to regulate visitor flows within the reception capacities of tourist sights and attractions [4, 11]. In the past, tourists within a destination were often guided by road and route signs or maps. Nowadays, this is where digital visitor management comes in [13]. The prerequisite is the structured development of a guidance and orientation system. On this basis, guidance measures can be implemented along the

customer journey (CJ). These are based, among other things, on networked sensor technology or mobile radio data, which is brought to guests at virtual and physical customer contact points through a special provision of information. This approach is referred to as nudging or sorting [3]. A nudge therefore refers to a measure that triggers a change in the behavior of those affected in a desired direction without limitations or obligations. This is achieved by consciously shaping the context-relevant decision-making aspects of the environment or surroundings for people [14].

An effective nudge requires an effective change in people's behavior. In the Fogg Behavior Model for persuasive design, the relationships between motivation, ability to act and prompting are defined as drivers of human behavior [7]. The main idea is that for a person to perform a target behavior, he or she must (1) be sufficiently motivated, (2) have the ability to perform the behavior, and (3) be triggered to perform the behavior (ibid.)

3 Method

3.1 Research Approach

In this study, we seek to provide a preliminary analysis of the research question with a survey containing an AB-test [12]. Therefore, we designed a survey that contains a small experiment with two subgroups A and B. The survey provides first insights into the current level of knowledge and attitudes of respondents towards AR.

3.2 Design of the survey and the experiment

This study evaluates the functionality of an AR guide as a visitor guidance tool in Füssen, Germany. For this purpose, an exemplary AR guide mock-up was developed as a route recommendation. The usual route is the main shopping road with sightseeing in the pedestrian zone. The alternative route is also a pedestrian zone with shops and sightseeing, however, less frequented. One of the two versions of the guide contains a nudge towards the alternative route (cf. Fig. 1).

The design of the AR-guide is based on the Fogg Behavior Model [7]. The AR-Guide in Füssen combines the following nudges: simplification, default rule, social norm [8]. An alternative offer is created that

uses digital information and bids as visitor guidance measures. After the experiment, we asked about previous AR experiences, openness to an AR guide, individual information search preferences and the use of digital applications in a tourism context. Finally, we asked for demographic data.

Fig. 17. AR-Guide with nudge (left images 1 & 2), without nudge (right).

3.3 Data

Prior to the distribution of the survey, we pre-tested the survey with 10 participants, leading to the clarification of several questions. During the data collection, 115 people over 15 years completed the online survey. The age limit is justified by the fact that potential visitors must have a mobile device for the AR Guide and a general understanding of AR. We did not focus on a holistic balancing of the data set, since this sample is only considered a preliminary study (done via LimeSurvey).

Table 11. Demographic and basic data

Basic Feature	Sample Group	Percentage (%)
Gender	Female	67
	Male	33
Age	15–20 years old	4
	21-30 years old	70
	31-45 years old	10
	46-60 years old	12
	>60 years old	4

Been at location of experiment	Yes	53
	No	41
	Not sure	6

4   Preliminary results and future research

In the following, we seek to illustrate first results of the preliminary study, leading to pathways for future research:

1. Nudging via AR might have positive effects on increasing the attractiveness of lesser-known destinations, and thus, on balancing visitors. The data indicates a link between the presence of a nudge and the choice of an alternative route ($\chi 2 = 5.58$, $p < 0.05$). However, in-depth research on the choice behavior of visitors in the context of AR visitor guides is required to entangle the complex relationship of the nudges and the steering effect. Furthermore, research on the effect of different nudge designs is required to understand the effect of content design on the steering effect via AR guidelines.
2. The most common reason to reject an alternative route was "concerns about quality" as well as the wish to visit "the most popular and best-known routes in the city". Only one person mentioned a lack of interest in AR content. This might indicate, that the success of alternative routes has less to do with the components of the digital applications and more to do with the content design and the range of alternative routes on offer.
3. In general, the "preference for less visited destinations" was quite large. This finding is significant for the development of a visitor guidance measure, as exemplified in this paper and already reflected in literature [9]. Participants mentioned "interest in new and exciting locations" and "gaining new knowledge about the city". The predominantly chosen motives are indicators of the attractiveness of lesser-known destinations and should be considered when designing the content.

5   Conclusion, limitations, and pathways

The paper focused on the potential of nudging in AR guides for visitor management. Its results indicate potential in this research stream although the data limits the generalizability of the results.

This leads to the limitations of the paper. First of all, the present data set is small and unbalanced. Thus, it is not well suited to produce reliable results. Second, the survey did not observe the real behavior of visitors but asked them about it in a survey. Thus, we propose the following pathways for our experimental study: researchers should aim towards varying the design of the nudge in the AR guide to gain a better understanding of the effect of the underlying design elements in a well-balanced data set. Furthermore, one might set up a real-world experiment to observe the decision-making of visitors using an AR guide influenced by appropriate nudges.

Despite its limitations, the paper seeks to open promising pathways for future research regarding nudging in AR visitor guides and illustrates the potential of nudging in AR visitor guides.

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VR through the tourism customer journey: expanding UTAUT2 with Anticipated Emotions

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1 Introduction

Virtual Reality (VR) is transforming destination marketing [9] through the introduction of immersive experiences, which can enhance visitors' engagement and generate business opportunities [3]. Such experiences can create a deeper connection with visitors, eliciting affective responses, improving both online and on-site experiences, thus generating customer value. Immersive technologies, with their experiential nature, can be particularly impactful for heritage sites, and positively contribute to their competitiveness. For these reasons, practitioners and scholars are interested in studying its adoption to (i) identify the factors that influence consumers' intentions to adopt this technology, and (ii) validate existing theories in the context of this emerging technology, to better explain its adoption patterns in the field of destination marketing. Current literature on VR in destination marketing can be split into five main areas of investigation, each related to one fundamental question: What, Who, How, Why, and When. While the first three macro questions appear to be extensively investigated, Why and When are not. Although it is well clear "Why" destination managers should offer VR solutions, there is still a lack of understanding of why tourists should live them [4].

Research on VR adoption in destination marketing has so far focused on functional drivers such as content design, sensory stimulation, or authenticity. However, while literature acknowledges the importance of the emotional dimension in immersive experiences [5], its impact on consumer behavior remains underexplored. This perspective has also a central role in the field of technology adoption, as traditional theoretical frameworks, such as the Unified Theory of Acceptance and Use of

Technology (UTAUT2), are criticized for not being able to fully model human behavior due to the lack of visibility on the emotional side, which is fundamental when investigating such experiential topics. In this context, Anticipated Emotions (AE) are used as complementary affective predictors of consumer behavior [6], given the significant influence of emotions on decision-making processes. Consequently, there is a clear research gap concerning the role of the emotional sphere in the adoption of VR within destination marketing. Investigating it is important, as it would provide tourism managers with insights that extend beyond the traditional functional drivers of adoption.

Furthermore, literature on VR in destination marketing highlights that there is limited research on the "When" dimension [4]. More specifically, it is clear how use cases differ based on the stage of the Customer Journey (CJ) [3,4,8], meaning that the cognitive and emotional processes influencing consumers' acceptance and intentions to use VR may differ before, during, or after a travel [4]. This highlights another gap in current research, namely exploring how the adoption processes vary across the different CJ stages. Taking a horizontal approach to the CJ, by investigating differences across its phases, would reveal important differences, thereby reinforcing the "When" dimension to extant literature.

To fill these gaps, this research explores the factors influencing consumers' intentions to adopt VR in destination marketing. The study has three main objectives: (i) applying the UTAUT2 model to VR adoption in destination marketing, (ii) testing the added value of integrating it with AE to better explain adoption dynamics, and (iii) evaluating how different stages of the customer journey influence the processes that shape consumers' intentions to adopt VR. To do so, we carry out a survey on a sample of 495 respondents, divided across three scenarios representing the stages of the customer journey (before, during, and after travel). This study aims to advance several contributions. From a theoretical perspective, it advances the current discussion about the application of technology acceptance models in destination marketing by expanding the UTAUT2 framework with AE theory. For tourism managers, the study seeks to identify the factors that influence consumer behavior and highlight how these factors vary across the customer journey, offering insights into what can be leveraged to foster the adoption of VR technology.

2　Conceptual model and hypotheses

Among the technology adoption theories, the UTAUT2 [10] is well accepted in the field of tourism. Developed as a consolidation of eight technology adoption theories, it aims to provide a unified theory capable of (i) explaining consumer intentions to adopt new technologies, and (ii) help managers assess the determinants of the success of their technology [10]. It features seven predictors of consumer behavioral intentions, five of which are relevant for VR in destination marketing. *Performance Expectancy* (PE) refers to the degree to which VR benefits visitors' activities such as obtaining information about a historical site or deciding whether to visit it or not. *Effort Expectancy* (EE) is the ease of using VR, *Social Influence* (SI) refers how much consumers perceive their peers believe they should use VR for tourism activities, *Facilitating Conditions* (FC) addresses consumers' perceptions of the resources and support to use VR (e.g., knowledge, internet access, etc.), *Hedonic Motivation* (HM) is the fun or pleasure derived from using VR. *Price Value* has been excluded from the study, as the focus is on usage behavior rather than purchase of VR devices, while *Habit* has been excluded due to not being applicable to such an emerging technology. Based on this evidence, we anticipate that all five predictors will positively influence a consumer's behavioral intentions to use VR when engaging with a tourism-related stimulus.

In the context of product adoption and usage, AE are used as affective predictors of consumer behavior [1]. Theory on AE builds upon the evidence that the emotional consequence of a decision is anticipated by consumers and is a relevant factor in the decision-making process [1], in which forward-looking anticipated emotions are elicited. AE are defined as prefactual appraisals in which a subject imagines the affective consequences of goal attainment and goal failure before deciding to act. AE can either assume a positive (e.g., happiness for goal accomplishment) or a negative (e.g., sadness for goal nonachievement) connotation, representing two separate constructs. Therefore, if a user imagines that using VR will make them happy, they will feel Positive Anticipated Emotions (PAE), and will be more likely to use it, aiming to attain the positive emotional outcome; while if they imagine that not using VR will make them sad, they will feel Negative Anticipated Emotions (NAE) and will subsequently be more likely to use it, trying to avoid the negative feelings associated with the privation of VR [1].

Building on this, we expect that both PAE and NAE will positively influence a consumer's behavioral intentions to use VR in response to a tourism-related stimulus. Also, we expect that combining cognitive predictors from UTAUT2 with affective predictors from AE will enhance the predictive power of both models [6].

Furthermore, attitudes and behaviors may differ based on the different use cases which can be identified before, during, or after a travel; therefore, distinguishing them is crucial to ensure reliability of the results [3,4,8]. Drawing on this, our model will also examine whether the stage of the customer journey mediates the relationship between the identified predictors and the behavioral intentions to use VR. The proposed conceptual framework is presented in Figure 1.
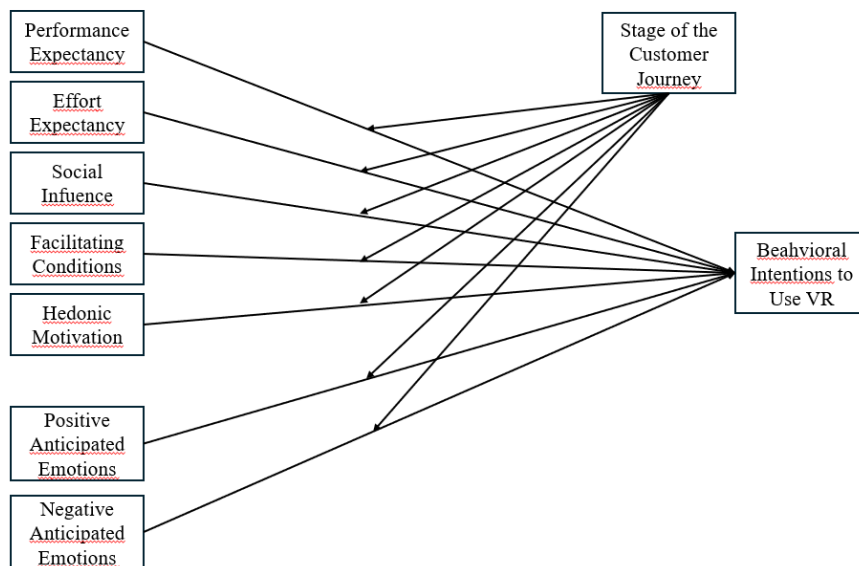

Fig. 18. Proposed theoretical framework

3   Methodology

An online survey was conducted in which participants were randomly assigned to one of the following scenarios based on current literature [3], related to a hypothetical visit to the Fori Imperiali historical site in Rome, Italy:

- Before the travel (S1): tourists can virtually pre-experience some spots of the location through VR, anticipating what they could visit in real life.
- During the travel (S2): while visiting the historical site, tourists can see, through VR, how the location looked during the Roman Empire, doing a dive into the past.
- After the travel (S3): once having come back at home, visitors can re-experience their visit through VR, recalling memories of their vacation.

The introductory section of the survey included a VR demo to ensure that all respondents had a clear understanding of VR technology. Following this, sociodemographic data, previous experience with the destination and VR technology were assessed to account for any potential confounding variables (single-item questions). Next, the specific scenario of VR use was introduced, accompanied by a manipulation check question to confirm respondents' awareness of the stage of the CJ they were assigned to. Lastly, the survey exhibited randomized items of the constructs from the UTAUT2 and AE theories, measured on 7-points Likert scales. Items regarding both theories have been measured through pre-validated scales [1,7]. Before distributing the survey, to ensure clarity and reliability of the questionnaire, a pre-test (N=30) has been carried out.

4   Results and Discussion

A total of 495 people aged between 18 and 45 (54% F, Mage=32,1, SDage=7,9) responded to the survey. Before testing the proposed model, all constructs have been checked for internal consistency reliability, ensuring that all variables had Cronbach's Alpha value higher than 0,7. Next, three linear regression models (M1, M2, and M3), featuring respectively predictors from the UAUT2, AE, and UTAUT2 and AE combined, have been tested. Results are presented in Table 1.

Results indicate that all the tested models prove to be significant (M1 R-adj=.761**, M2 R-adj=.615**, M3 R-adj=.781**) confirming the suitability of the chosen theoretical lenses. In the combined model, five predictors —Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, and Positive Anticipated Emotions— were found to be significant. Specifically, PE (β=.393**), HM (β=.273**) and PAE (β=.246**) are the primary drivers of Behavioral Intentions to adopt VR. FC and NAE show instead a lack of significance. Despite not having an adjusted R-square sensibly higher than M1, the most important theoretical contribution of M3 lies in the high predictive power of PAE, which confirms (i) it to be a significant predictor of consumer behavioral intentions, and (ii) confirm the added value of the integration of an affective component in the UTAUT2. Additionally, these findings provide practical insights for marketers, suggesting that strategies should highlight VR's practical benefits, the enjoyment it provides, and aim to generate excitement around the VR experience.

Table 12. Linear regression models.

Model	Construct	Beta	Sig.	VIF
M1	PE	0,47	<,001	2,513
	EE	0,072	0,022	2,032
	SI	0,114	<,001	1,392
	FC	-0,041	0,19	2,061
	HM	0,382	<,001	2,471
M2	PAE	0,782	<,001	1,153
	NAE	0,009	0,759	1,153
M3	PE	0,393	<,001	2,837
	EE	0,0	0,022	2,047
	SI	0,086	<,001	1,44
	FC	-0,039	0,198	2,062
	HM	0,273	<,001	3,141
	PAE	0,24	<,001	2,972
	NAE	-0,028	0,224	1,179

Regarding the role of the CJ phase, the moderation analysis has shown that PAE's impact on BI grows as consumers progress in the CJ (b_{S1}=.7021***, b_{S2}=.8058***, b_{S3}=.9096***), meaning that consumer behavior is growingly driven by emotions.

Our findings contribute to current literature on VR in destination marketing with three main theoretical implications. First, this study has deepened current literature on VR adoption in destination marketing, by

testing the UTAUT2 framework in this field for the first time, confirming the suitability of the model, and possibly laying the foundation for future UTAUT2-based studies on the usage of VR in destination marketing. Second, this study has proposed and tested a new, comprehensive framework that combines the UTAUT2 and AE. Results have shown that behavioral intentions are strongly driven by both cognitive and emotional factors, thus reinforcing the "Why" dimension to current literature on VR in destination marketing [4]. We also corroborate critiques to purely cognitive models, clarifying that emotions have an increasing impact on consumers' intentions through the customer journey and are complementary to cognitive factors. Third, our findings indicate the presence of an emotional trajectory related to consumers' intentions to adopt VR, in agreement with what was hypothesized by previous studies [4]. No significant moderation effect was found on UTAUT2 predictors, meaning once again that such perspective is not able to fully capture consumer decision-making processes regarding VR adoption in destination marketing. Therefore, our findings further corroborate critiques to technology acceptance models, and suggest the need for an emotional perspective. In doing this, we offer strong contributions to the "When" dimension of literature on VR in destination marketing [4].

This study also offers numerous implications for destination managers. First, it suggests that they should aim to provide tangible improvements to the visitor experience through VR. Moreover, they should aim to maximizing the ease of use associated with the usage of VR by, for instance, offering tutorials and instructions for visitors. It is also important to create a positive word-of-mouth by leveraging, for example, influencers. Additionally, it is crucial to offer a game-like experience to visitors, in order not only to make it interesting and useful, but also pleasurable and enjoyable. Finally, marketing campaigns should be designed with the goal of evoking positive emotions on consumers, showing, for instance, how VR allows to live enhanced, more powerful, life-like experiences. Moreover, our findings indicate that the impact of PAE grows as visitors move further in the customer journey, signaling the presence of an emotional trajectory that should leveraged by creating tailored marketing campaigns which resonate with the magnitude of the emotional motivators at each stage. In the first phase, efforts should be oriented to building anticipated excitement, in the second phase, communication should give a central role to the affective sphere of VR

experiences, while for the final stage managers should leverage travelers' nostalgia, emphasizing the possibility of reliving memories through VR.

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Dancing in the Digital: The Antecedents and Consequences of Presence in Virtual Reality Concerts

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Abstract. This study examines the impact of various forms of presence (social presence, telepresence, and temporal presence) on user experience in virtual reality (VR) concerts. We propose a theoretical framework where co-presence is a key element in VR concerts, influencing other forms of presence. Sixty-five participants were invited to attend a Tomorrowland concert using a Meta Quest Pro VR headset. Data analysis results show that co-presence positively influences social presence, telepresence, and temporal presence. In turn, social presence and telepresence are positively related to playfulness and attitude toward VR concerts, which subsequently affect the intention to attend future VR concerts. Contrary to expectations, social presence did not significantly influence playfulness, and temporal presence did not impact attitude toward VR concerts. Our findings underscore the importance of multidimensional presence in shaping user experiences and provide theoretical insights that can inform the design and development of more engaging VR concert platforms.

Keywords: Virtual Reality Concerts, Co-presence, Telepresence, Social Presence, Temporal Presence.

1   Introduction

The advancements in immersive technology enable the growth of virtual concerts, transforming how audiences engage with music performances. The proliferation of virtual reality (VR) concerts surged following the COVID-19 pandemic, as lockdowns and social distancing measures forced the entertainment industry to seek alternative platforms for live performances [1]. Artists and organizers turned to VR platforms like Fortnite and Wave to maintain live performances, offering immersive experiences to fans worldwide. These concerts allowed users to create avatars, interact with others, and explore virtual environments, enhancing engagement that is different from traditional concerts.

The pandemic highlighted VR's potential in the music industry, breaking geography and venue capacity limitations.

In VR concerts, attendees seek social engagement and the shared experience of live music performance, indicating that collective enjoyment is enhanced when visual social cues, such as synchronized movements, are present. However, most past studies focused on performer-audience interaction, not audience-audience interaction [2]. Therefore, the first objective of this study is to explore the effect of co-presence, the sense of togetherness, on concert experience. Moreover, many past studies have investigated telepresence or social presence (e.g., [3, 4]) in the context of VR concerts. Limited attention has been given to temporal presence. Hence, the second objective of this study is to provide a more holistic understanding of presence by including temporal presence—the feelings of audiences that they are experiencing the concert at present.

2 Literature Review and Theoretical Framework

2.1 Virtual Reality Concerts

Virtual reality has been widely adopted across numerous industries, including business for virtual meetings and training, education for immersive learning experiences, and gaming for interactive, real-world-like environments. The music industry has also adopted VR, particularly for virtual concerts, which allows users to attend immersive performances from anywhere in the world. In addition to social connectedness and engagement, seeing specific artists, the uniqueness of the experience, and the co-creation of the experience motivate people to attend virtual reality concerts [1, 5].

2.2 Presence in Virtual Reality

Co-Presence. Co-presence is "the subjective experience of being together with others in a computer-generated environment, even when participants are physically situated in different sites" [6]. The notion of co-presence is later extended to include the "perception of self" (one's awareness of the mediated other) and the "perception of the other" (the user's perception that the other is aware of the user) [7].

Social Presence. Social presence is defined as the degree of salience of the other person in mediated communication, which affects the interpersonal interactions between participants[8, 9]. Past studies have explored the feeling of social connectedness facilitated by virtual reality concerts [10, 11]. When the users are aware of others and their interactions in the virtual environment, they engage in deeper social interaction and a sense of involvement, allowing users to access others' thoughts, intentions, and sensory cues [12, 13]. Therefore, we propose *H1: Co-presence (perception of self and the other) is positively related to social presence.*

Telepresence. Telepresence is "the sense of being in an environment" [14]. In a virtual environment, the users have a sense of presence when completely immersed in a computer-mediated environment [15]. When users feel more co-present with their interaction partner, they are also likely to report experiencing more physical presence in the environment[13]. Therefore, we propose *H2: Co-presence (perception of self and the other) is positively related to telepresence.*

Temporal Presence. Temporal presence is defined as the feeling of being in the time of the virtual content [16]. Copresence can lead to shared understanding and co-construction of the experience, which makes users more attuned to temporal shifts in the virtual world as they coordinate their understanding and activities with others. The collaborative engagement can increase the feeling of "being in" the time of the virtual content, creating a stronger temporal presence. Therefore, we propose *H3: Co-presence (perception of self and the other) is positively related to temporal presence.*

2.3   Playfulness, Attitude toward VR Concerts, and Behavioral Intention

We define playfulness as the joyful feeling experienced during an activity, characterized by escapism from daily concerns and the pursuit of enjoyment [17]. As the level of presence increases, the VR environment becomes more elaborate, leading to more enjoyment [18]. Therefore, we propose *H4a: Social presence is positively related to playfulness*, **H4b: Telepresence is positively related to playfulness**, and *H4c: Temporal presence is positively related to playfulness.*

Moreover, users who experience a higher level of presence are more likely to demonstrate greater emotional engagement with the medium

and a more positive attitude toward its content [19]. Therefore, we propose ***H5a: Social presence is positively related to attitude toward VR concerts***, ***H5b: Telepresence is positively related to attitude toward VR concerts***, and ***H5c: Temporal presence is positively related to attitude toward VR concerts.***

The hedonic values have been proposed to positively affect an individual's continuance intention to attend future virtual events [4]. Positive attitude has also been theorized to be positively related to behavioral intention [20]. Therefore, we propose ***H6a: Playfulness is positively related to the intention to attend VR concerts***, and ***H6b: Attitude toward VR concerts is positively related to the intention to attend VR concerts.***

3   Methodology and Data Analysis

The study employed an experimental design followed by a survey. After reviewing several 360-degree videos on YouTube, we selected a Tomorrowland 360-degree concert video for our study. This selection was based on its clear visibility of the stage, the provision of a normal human eye-level perspective (unlike some 360-degree videos that offer perspectives higher than that of an average person), and the viewpoint originating from the audience's position, while some 360-degree videos position the viewpoint on the stage. We then set up a station at a university in Taiwan and invited passersby to participate in the study. The participants were asked to wear a head-mounted VR headset (Meta Quest Pro) to attend a Tomorrowland concert. The content of the Tomorrowland concert was obtained from a 360-degree video on YouTube. After they experienced one full song (nearly three minutes) during the concert, they were asked to complete a survey containing the constructs of interest in the study. Survey measures were adopted from previous studies. We recruited 65 participants, of whom 66% are female, 74% are between 18 and 24 years old, and most (66%) have experienced virtual reality before.

We employed partial least square structural equation modeling (PLS-SEM) for data analysis. We first evaluate the measurement model to ensure validity and reliability. Factor loadings, Cronbach's alpha, and composite reliability are all above 0.7. The average variance extracted (AVE) is all above 0.5, demonstrating satisfactory reliability and convergent validity. Heterotrait-monotrait ratios (HTMT) were all below

0.9, meeting the requirements of discriminant validity. We then evaluated the hypotheses using bootstrapping techniques. Three hypotheses were rejected (Figure 1). The model explains 60.3% of the variances of behavioral intention, and the model fit index (SRMR) is 0.084.
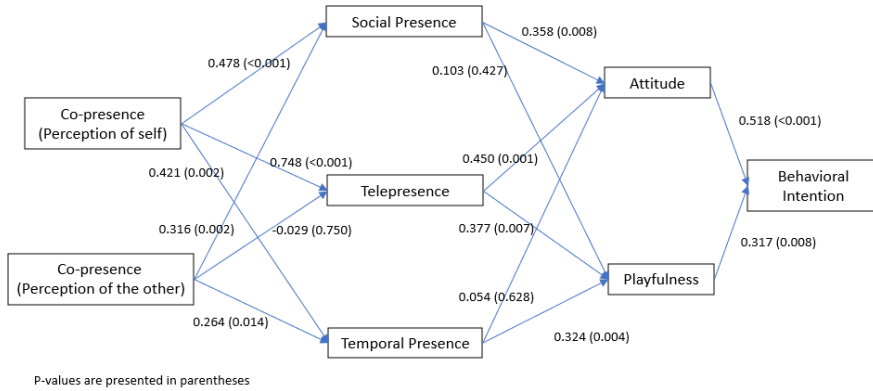

Fig. 19. Bootstrapping results

4 Discussion and Conclusion

70% of respondents viewed VR concerts as the future of the music industry, highlighting their accessibility and potential for positive experiences influenced by immersive levels [1]. In this study, we aim to evaluate the effect of different types of presence in VR concerts to provide a more theoretical understanding of the concept of presence. Contrary to our expectations, social presence does not significantly influence playfulness, while temporal presence does not impact the attitude toward VR concerts. This may be because the users might feel social frustration [21] during VR concerts, which negatively affects the enjoyment of the experience. On the other hand, temporal presence may be less influential to users' attitudes toward a VR concert compared to other immersive elements like visuals, interactivity, and social connections.

Future research should explore more antecedents of the sense of presence. In addition to co-presence, psychological involvement and behavioral engagement can also affect social presence, as the mere presence of the other without interaction may not contribute to the social pres-

ence [22]. The content of the VR concerts should also significantly affect the results. In this study, we employed a 360-video on YouTube. The next step in our research will be to create our own VR concert content to engage more interaction among the audience (e.g., the audience singing in unison, highlighting shared enthusiasm, or collective responses like clapping or cheering, demonstrating group excitement) with a more vivid visual display. To further evaluate the effect of the sense of presence, a control group that watches the 360-degree video on a mobile device or laptop (a less immersive version of the concert) can be employed. Finally, we measured the positive affect (playfulness) using a self-reported survey. Future research can use biometric sensors to measure emotional arousal during VR concerts to capture objective evaluations of users' responses.

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Tourist Cyberpsychology: Visual Appearance of the Travel Guide & Tourist Experience in Metaverse

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Abstract. The appearance of travel guides plays a role in tourist-guide engagement, affecting the overall tour experience. Metaverse provides innovative opportunities to develop virtual guided tours and shape the visual appearance of the guides' avatars. However, knowledge of the beneficial appearance of travel guides' avatars is scarce. This paper reports the results of the 1st stage of the study, which aims to explore tourists' experiences with travel guide avatars. The preliminary findings of the controlled experiment reveal that the alterations in the visual appearance of the travel guides' avatars, such as a smile, eye and hair colour, and the shape of the face, trigger diverse emotions, thereby enabling or sabotaging the tourist guide engagement. There is a need for a deeper understanding of tourists' cyberpsychology to ensure a positive tourist experience.

Keywords: Metaverse, Facial Expression Analysis, Emotions, Neuromarketing

1 Introduction

Guided tours serve as a key element of this experience by making it more personal, meaningful, and enjoyable. Guides play multiple roles in interactions with tourists [1]. A tour guide becomes a vital link, turning sights into stories with storytelling and transforming simple visits into rich, sensory explorations of the culture and history of the place. The appearance of a travel guide plays a crucial role in the tourist experience [2].
Metaverse is a technology-driven world that is expected to become the 3rd generation of the Internet and a "bigger outside" that lies beyond the space in which humanity operates nowadays [3]. It has the potential to amplify the everyday experience of individuals by providing them with a realistic, immersive and personalised space [4, 5]. Several destinations have already created a 3D copy of their space, enabling tourists to experience the attractions virtually [6]. Many travel guides have started offering virtual tours [7], thereby shaping tourist–guide interactions. Avatars serve as a manifestation of the user's identity to facilitate

engagement with others [5]. The appearance of an avatar can range from a basic icon to a highly customized realistic avatar that interacts uniquely with virtual environments. However, the effect of a guide avatar appearance on tourist experience, remains to be explored.

The study aims to explore tourists' experiences with travel guide avatars. Among others, it seeks to identify tourist emotions as a reaction to the travel guide avatars' appearance to further determine the influential facial features of the travel guide avatars. The preliminary findings of the controlled experiment reveal that the alterations in the visual appearance of the travel guides' avatars trigger diverse emotions, thereby affecting the tour's experience. There is a need for a deeper understanding of tourists' cyberpsychology and new standards for experience design in the digital environment.

2 Theoretical Background

2.1 Metaverse Guides

The appearance of the guide is known to play a crucial role in forming the tourist experience. It allows tourists to develop perceptions of the professionalism and credibility of the guide, thereby establishing a certain degree of engagement and trust with them [2]. It is not only the clothes but the guides' physical appearance that can influence tourists' perceptions of the tour quality and travel experience. Naturally, the presence of a smile on the guide's face has effect on tourists' perceptions of their approachability, knowledge and kindness. The shape of the guide's face and the presence of glasses can play a significant role in tourists' perceptions. Moreover, the effect of the physical parameters might vary among guides' gender [8, 9]. While such perceptions are likely caused by pre-existing stereotypes, they play a significant role in the tourist experience.

An avatar is a digital representation of an individual within the virtual world [10]. A user's avatar becomes a powerful means for expressing their identity through a chosen appearance [11]. Technically, avatars can have any visual appearance, e.g. a photorealistic, cartoonish, animal, or non-humanoid version [11]. It can range from a basic icon to a highly customized realistic avatar that interacts uniquely with virtual environments. Anthropomorphic avatars tend to be regarded as more reliable and appealing by users than, for instance, an animal or

non-humanoid version [10]. However, the effect of a guide avatar appearance on tourist experience, remains unexplored.

2.2 Tourist Emotions with Guides Avatars

The tourist experience constitutes the cognitive and emotional states, which can affect the tourist's engagement with the service and become a long-term memory [12]. Multiple concepts that aim to explain emotions and their effect on the overall experience currently co-exist [13]. Most scientists agree that a stimulus, such as an external event or a disruptive memory, triggers an involuntary emotion, which, in turn, affects the resulting experience and behaviour [14, 15].
Emotions are described by their type and strength [16]. The strength of an emotional arousal is measured by the amplitude of an emotional peak, and the length of the arousal [17]. In terms of the emotions typology, Ekman [13] introduced the concept of 7 "Basic" emotions (anger, surprise, disgust, enjoyment, fear, sadness and contempt). Cowen & Keller [18] argue that there are 27 distinct emotions that people may experience. Plitchik [19] argues that there are 8 primary bipolar emotions. Each of the primary emotions represents a dimension of sub-emotions (e.g. amazement vs surprise vs distraction) depending on the emotion intensity [15, 19]. Most of the studies also agree that emotions are neurophysiological reactions that were developed evolutionarily to regulate human behaviour and as a defence mechanism [19]. Observing individual emotions as a reaction to a stimulus can provide insights into the individual's experience and create an outlook into possible behaviour.

3 Methodology

The study took the form of a controlled experiment to enable the observation of avatars-triggered emotions. According to the research stream of Ekman, emotions are discrete feelings universally expressed worldwide via facial expressions [20]. 9 pairs of cartoonish avatars with humanoid characteristics were designed to represent the hypothetical appearance of a travel guide. The first pair presented a neutral human ap-

pearance with a neutral facial expression to be used as a control variable. The other eight pairs presented the modification in the physical appearance of the avatars (Fig. 1).

Fig 1. Designed Avatars of the Hypothetical Travel Guide

Among other data types, the study recorded the participants' facial expressions with a threshold of 80% probability and a length of 2 sec for each emotion. The eye-pupil movements were used to validate the data and eliminate emotional reactions caused by external stimuli. The experiment was performed in a laboratory with controlled light and temperature. The validated videos of facial expressions were used to perform facial expression analysis following Ekman's scale of 7 basic emotions (performed with Affectiva's AFFDEX automated coding). The study applied convenience sampling to acquire 60 valid cases. The selected participants identified themselves as experienced travellers who are also early technology adopters and are familiar with the Metaverse concept. Considering the idea of 7 basic emotions being universal, the study did not limit the participants by gender, generation and culture of the participants. At the moment of submission, the study analysed 21 valid observations.

4   Findings

The preliminary findings indicate that the participants' reactions are heterogeneous by the range and the strength of emotions, supporting the idea that even 7 basic emotions are highly individual and subjective occurring [14, 15]. However, it is possible to identify common trends in the emotions triggered by the avatars' appearance (Fig 2). Thus, joy prevailed over other emotions, indicating that most of the avatars were perceived as safe and engaging guides in the metaverse environment

[20]. The guides' avatars evoked a small degree of contempt, which indicates the participants asserting their status or power over the expected interactions with the guides' avatars. Negative emotions and surprise were present at a minimum level, indicating a generally positive attitude and readiness to the avatars, accordingly. The variations in the visual appearance of the travel guides' avatars triggered various emotional responses.
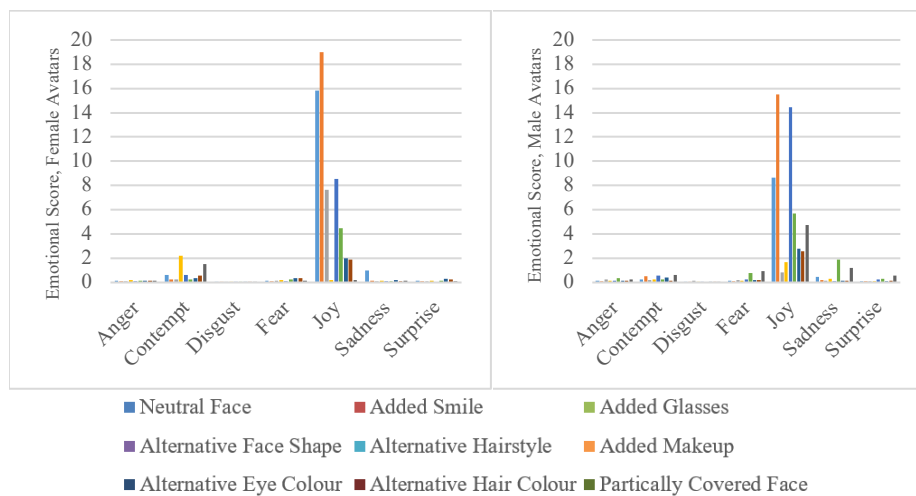

Fig. 2. Emotions Triggered by Travel Guides' Avatars

The neutral face avatar, which served as the baseline, elicited balanced emotional responses both for male and female avatars. Joy was a predominant emotion ($M_f = 15.84$, $M_m = 8.65$). Contempt ($M_f = 0.14$, $M_m = 0.61$), sadness ($M_f = 0.46$, $M_m = 0.97$), anger ($M_f = 0.14$, $M_m = 0.16$), and fear ($M_f = 0.16$, $M_m = 0.13$), disgust ($M_f = 0.03$, $M_m = 0.05$) as well as surprise ($M_f = 0.14$, $M_m = 0.09$) were present at a minimum level.

The added smile expectedly had a clear positive impact of the avatars. Thus, it increased joy (smile significantly increased joy ($M_f = 18.99$, $M_m = 15.53$), while reducing contempt ($M_f = 0.25$, $M_m = 0.50$), sadness ($M_f = 0.14$, $M_m = 0.18$) and fear ($M_f = 0.11$, $M_m = 0.12$) in comparison to the baseline. The scores indicate that the smile triggered the most positive reaction among all avatars' variations and the highest potential for engagement. An alternative hairstyle had a moderate emotional impact, with joy ($M_f = 8.56$, $M_m = 14.48$) and contempt ($M_f = 0.63$, $M_m = 0.58$) being comparable to the neutral face and Emotions like anger (M_f

= 0.11, M_m = 0.14), fear (M_f = 0.11, M_m = 0.27), and surprise (M_f = 0.06, M_m = 0.23) remained muted.

At the same time, the altered face shape triggered a lack of positive engagement and a possible threat as joy dropped (M_f = 0.21, M_m = 1.67), while contempt score (M_f = 2.23, M_m = 0.26) was the highest among the avatars. A similar reaction was observed with the avatars in glasses, with the altered eye and hair colour. The avatars in glasses triggered lower level of joy (M_f = 7.63, M_m = 0.86), but higher contempt (M_f = 0.26, M_m = 0.20). Similar reaction was observed with the avatars with the altered eye color: joy was notably low (M_f = 1.97, M_m = M = 2.8), while fear (M_f = 0.34, M_m = 0.19), contempt (M_f = 0.36, M_m = 0.41), as well as surprise in case an of female avatar (M_f = 0.28, M_m = 0.09). The alternative hair colour avatar also elicited similar reactions to the hair colour changes, particularly in fear (M_f = 0.33, M_m = 0.2) and surprise (M_f = 0.24, M_m = 0.13). Potentially, this indicates discomfort with the altered appearance.

Surprisingly, the added makeup also did not result in more positive emotions. Instead, it elicited notably higher fear (M_f = 0.27, M_m = 0.78) and slightly higher anger (M_f = 0.16, M_m = 0.34) and disgust (M_f = 0.22, M_m = 0.06), while joy (M_f = 4.46, M_m = 5.68) was lower than in other avatars. However, the avatars with partially covered faces triggered the most negative reaction. Joy was notably low (M_f = 0.20, M_m = 4.71), while contempt (M_f = 1.51, M_m = 0.61) was elevated compared to the baseline, suggesting that obscuring facial features led to discomfort or mistrust.

5   Discussion and Conclusion

The results of the first stage of the study reveal that travel guides' avatar appearance affects tourists' emotions. While the general emotional reaction to avatars is positive, the alterations in the visual appearance of the travel guides' avatars trigger diverse emotions. Some of the reactions were expected. Thus, a smiling face triggered joy and a partially covered face triggered contempt, similar emotional reactions in human-to-human interactions [8, 9]. However, some reactions were surprising. For example, glasses in human-to-human interactions are often associated with professionalism, leading to more engagement with the person. However, the avatars in the glasses elevated contempt, poten-

tially indicating mistrust and possible disengagement. Although the avatars' appearance alterations did not trigger strong emotions (M<20 on the 100-point scale), the findings indicate that it will affect the tourist experience in Metaverse.

As a result, the preliminary results contribute to the field of eTourism and use experience by providing new insights into tourist interactions in a digital space. At this stage, the causes of the emotional reactions remain unclear. There is a need for a deeper understanding of tourists' cyberpsychology, including the determinants of the virtual experience and possible cultural, gender and racial bias. The study's practical implications are related to the call for new standards for experience design in the digital environment. An advantage of the Metaverse environment is the technical possibility of designing avatars to support the tourist experience without violating ethical norms or supporting existing cultural, gender and racial bias. Future exploratory and explanatory research with larger samples and multiple contexts would be advantageous to ensure the success of Metaverse tourism.

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