Special Issue: The Economics of Artificial Intelligence in Tourism and Hospitality

TOURISM ECONOMICS
The Business and Finance of Tourism and Recreation

Tourism Economics
2026, Vol. 0(0) 1–25

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New face of platform capitalism in lodging industry: Who and where adopts platform-led loyalty tools?

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Abstract

Our study aims to identify segments of the lodging market influenced by platform capitalism, with a focus on the adoption of platform-led, AI-supported loyalty and marketing tools. The empirical objective is to examine the site-specific and situational factors that influence the variability in hoteliers' willingness to adopt AI-supported loyalty and marketing tools offered by Online Travel Agents (OTAs), as exemplified by the Booking.com's Genius programme. The analysis focusses on hotels, motels, and guesthouses that operate in Poland in 2024. The Random Forest Classifier was employed to identify feature-based impacts and spatial patterns in the adoption of OTA-led AI-supported loyalty and marketing tools. The findings suggest that the most popular hotels, located in metropolitan areas, offering higher-priced services and demonstrating greater awareness and knowledge of digital marketing and revenue management, are most likely to adopt OTA-led AI-supported loyalty and marketing tools.

Keywords

artificial intelligence, loyalty programmes, personalisation, platform capitalism, online travel agents, geographical volatility, Poland

Introduction

The advancement of artificial intelligence (AI) and big data analytics has become a prominent global issue. AI is transforming revenue management (RM) in the lodging sector, improving hotels' ability to predict market changes and personalise guest experiences, increasing loyalty and satisfaction (Ali et al., 2025). However, access to and control over AI-supported tools remain unevenly distributed, increasingly mediated by digital platforms rather than by hotels themselves. This transformation

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introduces potential risks, particularly for less privileged enterprises, local communities in disadvantaged and peripheral destinations, and the environment. Consequently, the influence of AI developments on loyalty management, marketing, and RM in the hotel industry warrants thorough consideration.

The emergence of big data has reshaped how information is processed across industries, including its use in loyalty and marketing strategies, which increasingly interact with and reshape RM practices (Kandampully et al., 2015; Talón-Ballestero et al., 2022), with AI integration redefining marketing paradigms through micro-targeting and predictive analytics (Durmuş Şenyapar, 2024). Traditionally, RM focused on pricing, demand forecasting, performance analysis, and distribution control (Denizci Guillet and Mohammed, 2015). To stay afloat and gain a competitive advantage, hotels must invest in innovative strategies to attract new customers and retain their customer base (Lentz et al., 2022).

AI-supported marketing tools that incorporate personalisation imrpove hotel operational efficiency and customer service, including experience, booking, and pricing, and consequently improve guest contributions to hotel financial and non-financial performance (Bilgihan and Ricci, 2024; Bulchand-Gidumal et al., 2024). The introduction of AI-supported RM systems has enhanced these functions in large hotel chains but remains largely inaccessible to independent hotels due to high costs. As a result, smaller properties often continue to rely on outdated or manual RM methods (Sun et al., 2025). AI tools such as machine learning (ML) algorithms, data analysis platforms, and predictive models are now widely used in marketing, customer experience, and operational efficiency across the tourism and hospitality industries (Doborjeh et al., 2022). In practice, AI-supported digital marketing enables real-time, precise, and engaging responses to guest needs, reinforcing personalised loyalty management (Kapoor and Kapoor, 2021).

In the consumer purchasing process, Online Travel Agents (OTAs) remain the most popular distribution channel for hotel rooms (Abrate et al., 2019). Within lodging, RM, AI, and big data analytics play a crucial role, particularly in OTA-led loyalty and marketing programmes that use AI for promotional optimisation and customer segmentation. Although these technologies offer significant operational efficiencies, they also pose risks for small and medium-sized enterprises (SMEs) and local communities in peripheral areas, potentially creating dependencies on OTAs – large multinational companies that possess the essential resources: data, technological infrastructure and expertise. This dynamic is often described as ‘platform capitalism’ (Srnicek, 2019), in which value creation, data access, and strategic decision-making are increasingly controlled by platforms rather than by service providers.

Despite the relevance of OTA-driven technology for digital pricing in the hotel industry, it has been largely overlooked in previous research. OTAs have generally been studied as sources of hotel pricing data (Pawlicz and Napierała, 2017), rather than as subjects in the context of RM strategies and practices (Altin, 2017; Altin et al., 2018). Our study aims to identify the factors that influence the adoption of the Genius programme by hotel facilities in Poland. It is guided by an empirical exploration of the Booking.com’s Genius loyalty and marketing programme and uses ML techniques to investigate the key features that shape hoteliers’ decisions. The adoption of the Genius programme does not equate to the adoption of AI-driven dynamic pricing systems. Instead, Genius represents an OTA-led loyalty and marketing programme that uses AI-supported promotional optimisation, offering an indirect lens on hotels’ engagement with platform-mediated marketing.

Aligned with this aim, we seek to address the question: “Who adopts AI-supported OTA-led loyalty and marketing tools, and where is this adoption concentrated?” Although the geographically differentiated adoption of AI-supported loyalty and marketing tools provided by OTAs remains the central focus, the study also contributes to the wider debate on platform capitalism in the tourism industry, particularly in relation to hotel facilities.

A key practical and social implication of this research is to moderate the prevailing enthusiasm surrounding AI developments in hotel loyalty management, marketing, and RM. By examining the control platform capitalism exerts over tourism destinations and lodging providers, this study aims to raise awareness among marketing and RM practitioners, destination managers, educators, and researchers.

Literature review

Digital transformation of marketing in the hotel industry towards AI-supported loyalty tools

Customers' perceptions of price and their subsequent decision-making processes are deeply rooted in their expectations and value evaluations (Kotler and Armstrong, 2014). They evaluate prices by comparing them to the most recent price or to what others have paid for a similar offer (Sahut et al., 2016). This price expectation and the actual price presentation are crucial in the choice process (Viglia et al., 2016). With the rise of generative AI models, the AI-supported digital revolution has accelerated at an unprecedented speed (Law et al., 2024). Technological tools, including AI, have made it easier for companies to apply strategies such as loyalty programmes (Koo et al., 2020).

AI-supported loyalty and marketing programmes may utilise hyper-personalisation, predictive modelling, behavioural targeting, and immediate engagement mechanisms; however, when delivered through OTAs, these capabilities are selectively applied and embedded within platform-controlled marketing architectures rather than fully delegated to hotels. Collectively, these elements can generate customer experiences that are deeply customised, contextually relevant and convenient, thus strengthening consumers' loyalty. However, paradoxically, the dilemma for hotels is that loyalty programmes are a considerable expense and yield less incremental revenue than expected (Lentz et al., 2022).

RM is an essential instrument in marketing management to match supply and demand by applying information systems and pricing strategies, delivering the right product to the right customer at the right time through the right channel at the right price (Ivanov and Zhechev, 2012; Viglia and Abrate, 2020). The digital turn in the hotel industry, including loyalty management, marketing, and RM, has been evident since the early 2000s. However, the digital transformation process was significantly accelerated by the COVID-19 pandemic (Bourdin et al., 2023; Lu et al., 2022). The pandemic also triggered widespread interest in the adoption of AI as a substitute for face-to-face service provision, although its effectiveness in replacing human contact remains contested (Jiang and Wen, 2020). The development of the Internet, social media, websites, smartphones, smart applications, and the overall virtual world has changed how information is distributed and how people plan and consume (Buhalis et al., 2023; Buhalis and Law, 2008; Dwivedi et al., 2024).

Hotel enterprises increasingly recognise many benefits of the digital shift, including enhanced operational efficiency, increased job satisfaction resulting from the elimination of routine and redundant tasks, and improved service quality and guest experience (Al-Hyari et al., 2023; Nam et al., 2021; Peng, 2020; Poroy Arsoy et al., 2024; Tan et al., 2025). With the integration of AI-powered systems, the scope and precision of product and service tailoring have expanded, enabling businesses to increase revenue, improve customer targeting, and adapt rapidly to market changes.

Personalisation, also known as one-to-one marketing (Arora et al., 2008), is a specialised form of product and service differentiation that is an essential element of the customer experience (Ozturk et al., 2017). Creating memorable and personalised customer experiences (also the purchase process) has always been at the heart of the service industry (Oyner and Korelina, 2016). By incorporating AI into RM, businesses can better understand and meet customer expectations, personalise their offerings, and optimise pricing strategies to improve revenue and profitability (Tomczyk et al., 2022). Instead of following a one-size-fits-all model, loyalty programmes based on personalised interaction enhance customers' perceptions of value, allowing rewards for the most valuable segments (Mitrović et al., 2022). The extensive use of personalised recommendations also greatly influences how customers search for and book hotel rooms, and the implementation of the strategy varies from hotel to hotel (Alderighi et al., 2022).

The development and integration of AI-supported tools has encouraged hoteliers to make loyalty programmes even more customer-centric. Personalisation and loyalty programmes in hotels go hand in hand to create unique, value-driven guest experiences, fostering repeat business and increasing revenue (Lei et al., 2024; Mitrović et al., 2022). This can encourage hoteliers to set the offers and prices at the customer level. Hence, price personalisation enhances pricing effectiveness by applying it at the customer level. Hotels recognise that each guest has a different value for the business, and guests perceive that their willingness to pay is being individually assessed. In addition, the application of AI in loyalty programmes can enable advanced experiments and simulations on the impact of both demand and supply on pricing (Brunato and Battiti, 2020; Tuncay et al., 2024). Consequently, further developments and improvements are expected in AI-supported marketing tools, driven by the need to increase the profitability of hotel operations.

Over time, loyalty management, marketing, and RM systems are set to become significantly more strategic and powerful, driven by advances in AI. AI will increasingly guide marketing and pricing decisions, enabling dynamic and highly personalised pricing tailored to guests' preferences. Automation will improve the management of inventory and distribution channels. RM will expand its scope to include forecasting, planning, tailoring, and coordination across suppliers and channels – maximising resource efficiency, revenue growth, and guest satisfaction. A move towards more centralised RM structures will support more effective resource allocation. The application of AI in RM will align with technological developments in other hotel operations, reinforcing a customer-first organisational and communication approach that seeks to optimise costs and maximise profitability (Smrutirekha et al., 2023).

However, this ongoing technological transformation has implications that pose potential threats, particularly for SMEs, peripheral communities, and the environment. Hence, the post-capitalist visions of disincorporated marketing and fair pricing are discussed (Kelleci, 2024; Napierała and Pawlicz, 2023). Against this backdrop, AI-supported OTAs initiatives – including the Genius programme investigated within this study – merit further clarification regarding their role in marketing and RM. Although the Booking.com's Genius programme is fundamentally a loyalty and marketing mechanism designed to improve property visibility and repeat bookings, it incorporates an optional 'Genius Dynamic Pricing' feature that is explicitly powered by ML technology to optimise discount timing and magnitude (Booking.com, 2025). This automated recommendation system differs from the traditional RM concept of dynamic pricing, which involves continuous real-time rate adjustments based on market demand and forecasting models. Participation in this ML-based feature is voluntary, and the broader Genius programme remains a rule-based loyalty and visibility framework.

Nevertheless, empirical research confirms that Booking.com increasingly integrates AI and ML capabilities into its operational processes (Tsai, 2023), situating Genius within a platform that is comprehensively AI-enabled. Consequently, the Genius programme should be regarded as an OTA-led marketing and loyalty tool that is partially AI-supported – through its ML-driven dynamic pricing function – and embedded in a wider AI-enhanced ecosystem built on algorithmic ranking, recommendation, and personalisation systems (Booking.com, 2024; Goldenberg and Albert, 2022; Mavridis et al., 2020). In conclusion, AI in the Genius programme does not set base prices, but enhances the visibility and competitiveness of rates already determined by hoteliers. This distinction mirrors broader trends in digital pricing and RM, where advances in data analytics and segmentation enable near-perfect price discrimination while also raising concerns about transparency, perceived loss of control, and the complexity of implementation (Baumgart, 2020).

AI is ineffective without careful attention to the data collection process, ensuring data reliability, and a thorough understanding of the technology. This includes not only technical aspects, but also legal and ethical considerations, as well as domain-specific knowledge where AI is applied (Maroyan, 2024). Consequently, the digital transformation in marketing and RM is a much broader process than a purely technological one. The radical transformative nature of AI means that its application to a single process within a single industry (e.g., marketing and RM in the hotel sector) can have much broader economic and social consequences (Buccella, 2023).

OTAs' actions within digitalised marketing, resulting in risks and challenges, and hotels' responses

Digitalisation in the hotel industry offers new opportunities to enter emerging markets by improving visibility and attracting new guests. This includes the digitalisation of data collection, the decision-making process, and the expansion of online distribution channels. OTAs are best understood as 'lean platforms', 'virtual platforms', or 'asset-less companies' whose key assets are software and data analytics. Operating through a hyper-outsourced model, these platforms externalise nearly all services and resources. Their success stems directly from control over user relationships, enabling the generation of monopoly rents (Clemons et al., 1999; Del Romero Renau, 2018; Srnicek, 2019).

OTAs' algorithms play a crucial role in shaping the value and visibility of tourist spaces, influencing perceptions and booking probabilities. Although algorithmic decision-making is often believed to reduce human error and bias, research suggests that these systems can actually reinforce social and spatial inequalities (Roelofsen, 2024). Contrary to initial expectations among economic geographers, the digital shift has not decentralised economic activity. Instead, it has reinforced platform capitalism, fundamentally transforming spatial organisation and related economic, social, and political dynamics (Kenney and Zysman, 2020).

Platform capitalism reshapes how value is created, who benefits from it, and where it is captured – highlighting asymmetrical power relations between platforms and their ecosystem of users and stakeholders, including guests, hoteliers, local communities, and the environment (Kenney and Zysman, 2020; Sigala, 2022). Three configurations of platform capitalism have been identified globally: market-led capitalism (e.g., the United States), panoptic control societies (e.g., China), and commons monitored by citizens (partially pursued in EU member states). In the latter, information is treated as a regulated good positioned between private and public domains (Boyer, 2022).

Due to the limited adoption of technological innovations in loyalty management, marketing, and RM, control over revenue-generation strategies, policies, and tactics may increasingly shift from hotels to OTAs, creating various risks (Alrawadieh et al., 2021; Mazaraki et al., 2022). These risks primarily affect SMEs (Wei and Pardo, 2022). Many hoteliers perceive this shift as undermining their autonomy and self-regulation capacity. Professionals note a potential contradiction: on the one hand, platforms enable access to new markets; on the other, they reduce independence by enforcing commission policies and pricing logic (Surdez et al., 2024). Consequently, competition is moving away from traditionally regulated markets toward platform-dominated structures. AI-powered marketing and RM tools, while boosting platform profitability, further reinforce monopolistic tendencies and contribute to the commodification of both tourism experiences and spaces (Clemons et al., 1999; Del Romero Renau, 2018; Srnicek, 2019).

Recent scholarship has shown growing interest in the application of AI in RM (Binesh et al., 2021; Peng, 2020). However, researchers in fields such as marketing and management often exhibit overly optimistic perspectives, frequently downplaying the risks and unintended consequences of AI development (Belanche et al., 2024). Several negative impacts of AI have been identified in service industries – including tourism and hospitality. These include: (1) unclear accountability for AI-supported decisions and associated legal risks (e.g., restorative justice in algorithmic crimes); (2) breaches of customer privacy and data security; (3) reduced social and human interaction, which weakens customer-firm relationships; and (4) widening social inequality and exclusion for both guests and employees (Bakir et al., 2025; Barari et al., 2024; Gursoy and Cai, 2025; Hadzi, 2022; Millauer and Vellekoop, 2019; Vatankhah et al., 2024).

Price personalisation and loyalty programmes are inherently connected, as loyalty data provide the behavioural insights needed to customise pricing and offers, thus improving guest satisfaction, strengthening loyalty, and optimising revenue performance (Lentz et al., 2022). However, the adoption of AI-supported pricing strategies carries potential risks, as algorithms can misinterpret customer preferences or willingness to pay, leading to forms of price discrimination that guests may perceive as unethical or unfair (Tomczyk et al., 2022). Nevertheless, given that consumers are increasingly knowledgeable and capable of comparing rates across platforms, maintaining rate parity remains essential to safeguard customer trust and prevent adverse effects on loyalty (Lentz et al., 2022).

The challenges of AI adoption in hotels are not addressed adequately. It is often argued that AI tools support transactional rather than relational service models and do not enhance interpersonal aspects of the guest experience (Belanche et al., 2024). Obstacles include the need for high-quality data, the difficulty of aligning AI systems with human staff, and the high costs of integrating AI into daily operations (Bulchand-Gidumal et al., 2024). Hotel loyalty, marketing and RM strategies to overcome these challenges operate across technological, organisational, financial, and guest-experience dimensions: (1) technologically, hoteliers demand user-friendly and compatible automation solutions; (2) organisationally, internal capacities – knowledge, skills, and employee readiness – are critical; (3) financially, the cost of comprehensive AI integration is a significant barrier; and (4) experientially, preserving human interaction remains a core concern, especially in high-end hospitality (Khlusevich et al., 2024; Koo et al., 2021; Tan et al., 2025).

According to Balk (2024), SMEs in the hotel industry typically accept the well-established dominance of OTAs. Although many hotels are seeking to reduce their reliance on these platforms, they remain uncertain about the effectiveness of these efforts. Interestingly, these enterprises show strong awareness of cooperative initiatives, yet they tend to prioritise traditional, non-digital forms of collaboration over digital cooperation.

The geographical dimension of these developments has received limited attention. Even the most comprehensive bibliometric studies on service industries (e.g., Vatankhah et al., 2024) tend to neglect spatial considerations, including the emergence of territorial disparities and the weakening of cohesion due to AI-driven tourism management. The primary argument for a more geographically informed analysis is that small and medium-sized independent hotels in peripheral regions often deliver distinctive, culturally rich experiences that distinguish them from global chains and generic mass tourism destinations. These offerings foster stronger connexions to local culture and heritage (Tan et al., 2025). Against this backdrop, analysing the spatial heterogeneity of digital transformation is essential for tourism studies (Zhang et al., 2025), as it directly shapes the resilience trajectories of destinations and their capacity for sustainable development.

OTAs are particularly appealing to guests who travel infrequently or lack loyalty to specific hotel brands, as they provide access to a wide selection of options in every destination (Koo et al., 2021). OTAs increase user satisfaction and trust through loyalty programmes that incorporate personalised discounts (providing a sense of getting the best deal), bundled services (offering comprehensive support), active data-driven engagement (promoting mutual interests), and gamification (creating hedonic and entertaining online shopping experiences) (Baumgart, 2020; Lu and Ahn, 2024; Shi et al., 2022). However, OTA customers are often 'brand-agnostic', showing stronger loyalty to platforms than to individual hotels (Raab et al., 2018).

Programmes such as Booking.com's Genius target loyal customers with tailored offers and improved visibility, which indirectly shape hotels' revenue strategies but do not represent dynamic pricing systems. The distinction is important: Genius functions as a visibility and loyalty enhancement mechanism, rather than as RM or dynamic pricing system in its own right. In this study, Genius is not analysed as a pricing tool but as an AI-supported loyalty mechanism that shapes visibility and guest engagement, thus influencing hotels' marketing and distribution strategies. These benefits substantially intensify the competitive challenge faced by independent hoteliers. Therefore, further research is warranted on the growing influence of OTAs and the development of strategic responses by hoteliers (Binesh et al., 2021; Koo et al., 2021).

Site and situational factors influencing the adoption of AI-supported loyalty and marketing tools provided by OTAs

This study aims to identify the factors that influence hoteliers' willingness to adopt AI-supported loyalty and marketing tools offered by OTAs. The adoption is treated as the dependent variable, while the following site-specific and situational characteristics are examined as independent variables in the proposed model: hotel size, hotel standard and guest satisfaction, service price level, location, and hoteliers' awareness of RM principles. The selection of independent variables is similar to that used in ongoing studies by Bertrand et al. (2025).

The size of the hotel is directly related to the availability of technological, organisational and financial resources necessary for the successful implementation of AI-driven technologies, including loyalty management, marketing, and RM (Khlusevich et al., 2024). The size of the hotel may be measured directly by the number of rooms or, where this information is unavailable, indirectly by the number of guest reviews. It has already been confirmed that smaller hotels tend to generate a higher ratio of reviews relative to their size (measured by the number of rooms), indicating greater effectiveness in prompting feedback. However, despite this advantage, the total number of reviews remains higher for larger hotels due to their greater capacity and volume of guests (Martin-Fuentes, 2016; Mellinas and Martin-Fuentes, 2019; Molinillo et al., 2016).

Hotel standards directly impact guest satisfaction. Therefore, the measures of both phenomena are to some extent interconnected. Although the criteria for hotel star ratings vary geographically between countries and between the official and OTA systems (Pawlicz and Napierała, 2017), a relationship has been observed between these ratings and customer satisfaction, as reflected in the review scores. Standards can also be inferred from variables such as room size (Castro et al., 2016; Israeli and Uriely, 2000) or the availability of thermal control features such as air conditioning (Zhang et al., 2023). The higher hotels' objective, perceived standard, and market position, the greater guests' expectations for AI applications, and the stronger the willingness and capacity of hoteliers to adopt such technologies (Nam et al., 2021).

A positive correlation between the application of AI-driven technologies and the operational efficiency of hotel facilities – including Average Daily Rate (ADR) – has already been established (Peng, 2020). Furthermore, hotel pricing tends to align with both star category and guest satisfaction levels (Martin-Fuentes, 2016). On the other hand, the highest-rated, highest-ranked, and most expensive luxury hotels may be more cautious about the risks associated with automating processes that rely on human interaction and directly shape the guest experience (Khlusevich et al., 2024).

Higher-end and chain-affiliated hotels, typically equipped with more robust technical and human resources, are more likely to implement such tools (Nam et al., 2021; Napierała et al., 2020). The use of OTAs as a distribution channel encourages hotels – particularly those with higher star ratings – to adopt advanced marketing and RM techniques (Melis and Piga, 2017). For independent hotels in particular, OTAs represent an accessible entry point into AI-assisted loyalty management, marketing, and RM, although successful integration requires strategic alignment to maintain pricing integrity. OTAs are also frequently regarded as the most effective distribution channel, even in comparison to direct bookings (Manousakis and Mattas, 2020).

Both distance from the regional centre and local population density are considered geographical variables used to assess the location of a hotel as central or peripheral (Copus, 2001). Binary variables, such as whether breakfast is included in the room rate or whether the offer is refundable, provide indicators of the experience of the person responsible for RM strategies. Excluding additional services from OTA listings reduces the commission payable and allows hotels to attract guests at lower, more visible prices (Biełuszko and Marciszewska, 2018). Meanwhile, non-refundable offers are often strategically reserved by hoteliers for exclusive deals offered via direct booking channels (Toh et al., 2011).

In summary, prior research has examined the role of AI in loyalty management, marketing, and RM broadly but has overlooked the role of OTA-led loyalty programmes such as Genius. Although these tools combine marketing visibility with AI-supported promotional optimisation, little is known about which hotels adopt them and where their adoption is concentrated. This study addresses this gap by applying a Random Forest Classifier and spatial analysis to hotel-level data in Poland. The analysis is grounded in platform capitalism theory (Boyer, 2022; Srnicek, 2019) and in the literature on digital inequalities (Kenney and Zysman, 2020; Roelofsen, 2024), extending these frameworks to the context of AI-supported marketing and RM in hospitality. This responds to recent calls to examine AI adoption in OTAs more closely, as they increasingly shape market structures, cost strategies, and hotel-guest relations (Hernández-Tamurejo et al., 2025).

Two contradictory assumptions should be mentioned. First, the general approach to implementing AI-supported technology depends on various knowledge and financial resources, which are most commonly available in large, chain-affiliated hotels of a higher standard and service price level, centrally located, and managed by staff who are more aware of RM principles (Nam et al., 2021; Napierała et al., 2020; Sun et al., 2025). Second, the implementation of OTA-provided loyalty and marketing programmes is considerably easier and less demanding in terms of the aforementioned knowledge and financial resources. Hence, it is expected that the integration of the investigated programmes will be more common in small independent hotels of a lower standard and service price level, peripherally located, and managed by staff who are less aware of RM principles. This assumption aligns with the general tendency towards OTA dependency and the risks related to the loss of hotels' autonomy observed on a larger scale in this group of hotels (Balk, 2024; Martin-Fuentes and Mellinas, 2018; Surdez et al., 2024). However, contradictory results are reported by Atanasova and Ivanov (2021), who confirm that Bulgarian hotels that are more dependent on OTAs are also more eager to use professional RM tools. These hotels are also characterised by a higher number of rooms, a higher category, cooperation with a higher number of OTAs, and the use of higher prices when selling their services.

Methodology

Data collection and processing

Hoteliers – when enabling digital marketing and pricing – can theoretically adopt one of the following approaches: developing the technology in-house, adopting technology provided at a centralised or corporate level (e.g., by a hotel chain), using tools offered by third parties (e.g., OTAs), or employing a mixed approach (Altin, 2017; Altin et al., 2018). Depending on the chosen approach, the challenges and benefits of digital marketing and pricing will differ. When using the technology provided by OTAs, the entry threshold is relatively low in terms of both financial and human resources. However, the benefits are also limited, as the algorithms are designed to serve the interests of platforms rather than those of individual users (Srnicek, 2019).

This study focuses on Booking.com's Genius programme, which uses ML to manage guests' loyalty, support marketing, and suggest optimal pricing decisions (Booking.com, 2025). The Genius programme represents the most accessible tool, compared to the other approaches outlined above, that enables any hotel to implement digital marketing and pricing. Still, our aim is to identify which hotels participate and which do not, the characteristics of these hotels, and finally, the spatial patterns that define hotel willingness to participate in the AI-supported Genius loyalty and marketing programme offered by Booking.com. The decision to focus on Booking.com is supported by the fact that the company has been designated as a *gatekeeper* for its online intermediation services by the European Commission (2024). This designation serves as a formal confirmation of its dominant position and structural power within European tourism markets.

Data were collected from Booking.com for the entire territory of Poland using Octoparse (Octopus Data Inc, 2024), a web-scraping application. The data cover lodging entities – hotels, motels, and pensions – which are collectively classified as hotel facilities under Polish law (Ustawa z dnia 29 sierpnia 1997 r. o usługach hotelarskich oraz usługach pilotów wycieczek i przewodników turystycznych [Act of 29 August 1997 on hotel services and the services of tourist guides], 1997). However, it should be clarified that on Booking.com, the use of these categories is declarative in nature. The platform does not require formal confirmation that an establishment officially belongs to one of the specified types. With this in mind, some other lodging entities can mislead guests by classifying themselves under the officially defined categories of hotel facilities.

The dataset includes site features such as price, star rating (ranging from 1 to 5, with non-rated hotels classified as 0), overall guest rating (from 1 to 10), number of guest reviews, room size, and a set of dummy variables indicating whether breakfast is included in the price, the offer is non-refundable, the room is equipped with air conditioning, and the lodging entity is part of a hotel chain. Situational factors such as distance from the regional centre and local population density are also used.

After scraping the Booking.com website and curating the dataset (including duplicate removal), 3797 hotel facilities – hotels, motels and guesthouses – operating in Poland were identified for bookings made on 24 August 2024 with a check-in date of 16 October 2024. The dates were deliberately chosen, as previous research confirms that, in Poland, the best price model estimations are observed on working days in autumn (Pawlicz and Napierała, 2017). The detailed characteristics of the dataset can be found in Table 1.

Data analysis

The Random Forest Classifier (Scikit-learn Developers, 2024) was used to identify the characteristics of lodging entities that significantly affect their willingness to participate in the AI-supported Genius

Table 1. Site and situational factors that influence hoteliers' willingness to adopt the AI-supported Booking.com's Genius programme.

Variable	Characteristic	Basic summary of the dataset
Hoteliers' willingness to adopt AI-supported marketing and RM tools (dependent variable)	Percentage of hotel facilities adopting the AI-supported genius loyalty and marketing programme [%]	35.4
Price	Average best available rate for a double room with check-in on 16 October 2024 [PLN]	358.2
Star rating	Percentage of hotel facilities [%]:	
	- 5-star	2.4
	- 4-star	12.1
	- 3-star	28.8
	- 2-star	6.1
	- 1-star	2.5
	- Non-rated	48.1
Overall guest rating	Average overall guest rating	8.6
Number of guest reviews	Average number of guest reviews	1035.8
Room size	Average room size offered [sq m]	22.6
Breakfast included	Percentage of offers including breakfast in the price [%]	34.5
Non-refundable	Percentage of non-refundable offers [%]	48.9
Air condition	Percentage of offers with rooms equipped with air conditioning [%]	38.6
Chain affiliation	Percentage of hotel facilities affiliated with a hotel chain [%]	8.2
Distance from the regional centre	Average great-circle distance from the hotel to the nearest regional authority headquarters [km]	42.8
Local population density	Average population density of the municipality where the hotel is located [persons/sq km]	1022.2

Source: Own elaboration based on data collected from Booking.com using Octoparse.

loyalty and marketing programme offered by Booking.com. Hence, the applied method enables the identification of the features that most significantly influence the willingness of a lodging entity to delegate part of its control over loyalty management, marketing and RM to AI tools powered by OTA, thus contributing to the development of platform capitalism. The Random Forest Classifier, as an ensemble of multiple decision tree classifiers, is well-suited for this analysis due to its robustness in handling complex, non-linear relationships between variables (Pal, 2005; Pedregosa et al., 2011).

Among 3797 hotels identified in a dataset, 2177 were included in the training set to run the Random Forest Classifier. The native strategy built into the Random Forest Classifier for handling missing values was used, which involves testing different ways of assigning missing values to splits (branches) in the tree to create more apparent divisions (Pedregosa et al., 2011). The main parameter of the Random Forest Classifier – max depth – was selected using a grid search hyperparameter tuning procedure. The best estimator had four levels, which effectively limited its complexity and facilitated explainability.

The geographical approach of this study involves not only the inclusion of geographical attributes in the analysis but also a cartographic examination of the spatial patterns identified through the Random Forest Classifier. Specifically, spatial variation in the adoption of the AI-supported Genius programme was assessed through a cartographic analysis of the nodes in the tree-based classification model mentioned above. A separate map of hotel facilities was generated for each node, splitting the investigated sample according to the observed value of the selected independent variable. Based on feature importance within selected branches, spatial patterns of adoption of the AI-supported Genius programme were identified. For spatial analysis, two of the most efficient branches – judged by their impurity reduction and size – were selected to represent the implementation and non-implementation of Booking.com's Genius loyalty and marketing programme in Polish hotel facilities.

This novel approach to geographic analysis enriches the discussion on the development of platform capitalism in the tourism industry by adding a geographical context. It also addresses the challenge of analysing spatially concentrated phenomena. Hotel facilities in Poland are predominantly located in the largest metropolitan areas, with significant rural regions showing a marked lack of such facilities (Napierała, 2019). In this case, discussions of spatial issues cannot be effectively supported by methods like Geographically Weighted Regression or similar approaches. The spatial analysis mentioned above is crucial to understand how local economic conditions, market dynamics, and platform capitalism influence decision-making in the hospitality sector.

Empirical results

Factors influencing the adoption of AI-supported loyalty tools provided by intermediaries

The popularity of hotels, measured by the number of guest reviews, was identified as the most significant factor influencing the implementation of the Booking.com's Genius loyalty and marketing programme in Polish hotel facilities (see Table 2). The popularity of the hotel, as shown in the guest reviews, is linked to the number of rooms available for sale. Larger hotel facilities, with greater capacity, can accommodate more guests, and therefore receive more reviews. Consequently, larger hotels are typically participants in the Booking.com's Genius loyalty and marketing programme.

Table 2. Importance of site and situational factors in explaining the implementation of Booking.com's Genius loyalty and marketing programme in Polish hotel facilities: Results from a Random Forest Classifier.

Variable	Importance
Number of guest reviews	0.345
Price	0.231
Non-refundable	0.098
Overall guest rating	0.080
Distance from the regional centre	0.073
Local population density	0.052
Star rating	0.038
Chain affiliation	0.038
Room size	0.028
Breakfast included	0.012
Air condition	0.005

Source: Own elaboration based on data collected from Booking.com using Octoparse.

Room rates were identified as the second most significant factor influencing the positive adoption of AI-driven marketing and RM tools provided by OTAs. Conversely, the implementation of such tools may enable hotel facilities to achieve relatively higher room rates and, *ceteris paribus*, increased revenues.

The findings (see Figure 1) indicate that the most popular hotel facilities – located in metropolitan areas, offering higher-priced services, and excluding breakfast from the basic room rate – are the most likely to adopt the AI-supported Genius programme provided by Booking.com. A hotels' decisions to exclude breakfast from the basic price may reflect a greater awareness and understanding of principles of RM, as it avoids using Booking.com to sell additional services beyond accommodation, thus reducing commission costs.

Interestingly, hotels within a 100 km radius of metropolitan centres that offered the lowest rates were less likely to adopt AI-supported OTA-provided technology to support loyalty management, marketing, and RM decisions. The cheapest services, even when offered in central locations, appear to be outside the interest of platform capitalism. This suggests that AI-supported technology is directed towards entities (and, by extension, destinations) that prioritise revenue generation.

Spatial patterns of delegating control over loyalty management, marketing, and RM to AI tools

Many areas in Poland lack hotel facilities affiliated with the Booking.com's Genius loyalty and marketing programme, despite the presence of other accommodation providers. This is particularly

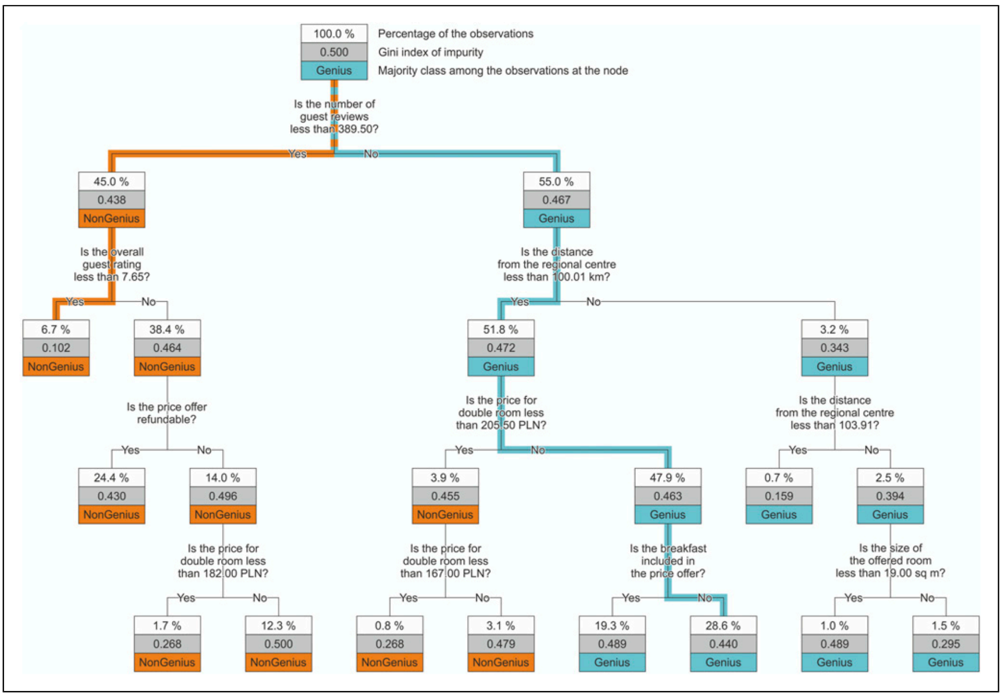

Figure 1. Impact of site and situational factors on the implementation of the Genius loyalty and marketing programme of Booking.com in Polish hotel facilities. Source: Own elaboration based on data collected from Booking.com using Octoparse.

evident in the peripheral regions of the country, especially in the border areas between administrative regions (see Figure 2), which are recognised as disadvantaged territories (Leśniewska-Napierała et al., 2019).

The dominant spatial pattern of delegating control over loyalty management, marketing, and RM to AI-supported technology provided by Booking.com is highly concentrated (see Figure 3). Human control over aforementioned processes appears less effective in disadvantaged areas, whereas AI-driven tools dominate in the most profitable tourism regions – particularly in large cities and major mountain destinations. A question that remains beyond the scope of this research is whether the Genius loyalty and marketing programme of Booking.com is the only tool used for loyalty, satisfaction, and revenue purposes, or whether it is implemented alongside other channels, with human oversight still playing a role in the broader process.

Small and low-rated hotels operate outside of the Booking.com's Genius loyalty and marketing programme (see Figure 4). This suggests that low ratings may, to some extent, result from ineffective or absent loyalty, marketing, and pricing policies, with prices potentially perceived by guests as unfair. In particular, such hotels are more randomly distributed in the study area. However, this type of facility can be found in both peripheral regions and urban areas, which are generally characterised by higher concentrations of hotel infrastructure.

Discussion

Theoretical contributions

The most important theoretical contribution, as well as the novelty of the study, lies in the fact that this is the first research to examine hotels' dependency on platform-led AI-supported loyalty tools. Although there is a substantial body of research examining loyalty to OTAs and loyalty to hotels separately, to date little is known about the nature and characteristics of hotels willing to use OTA-provided, AI-supported

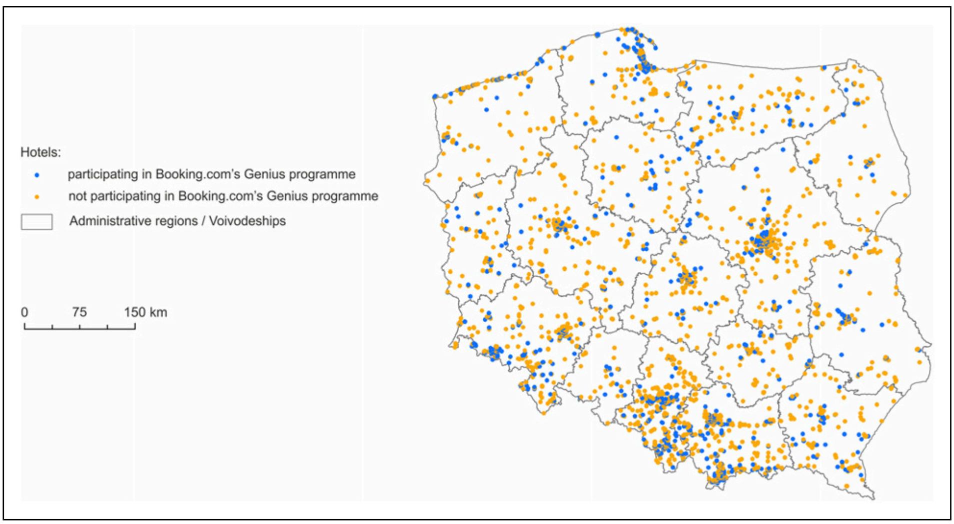

Figure 2. Location of hotel facilities participating in (and not participating in) Booking.com's Genius loyalty and marketing programme. Source: Own elaboration based on data collected from Booking.com using Octoparse.

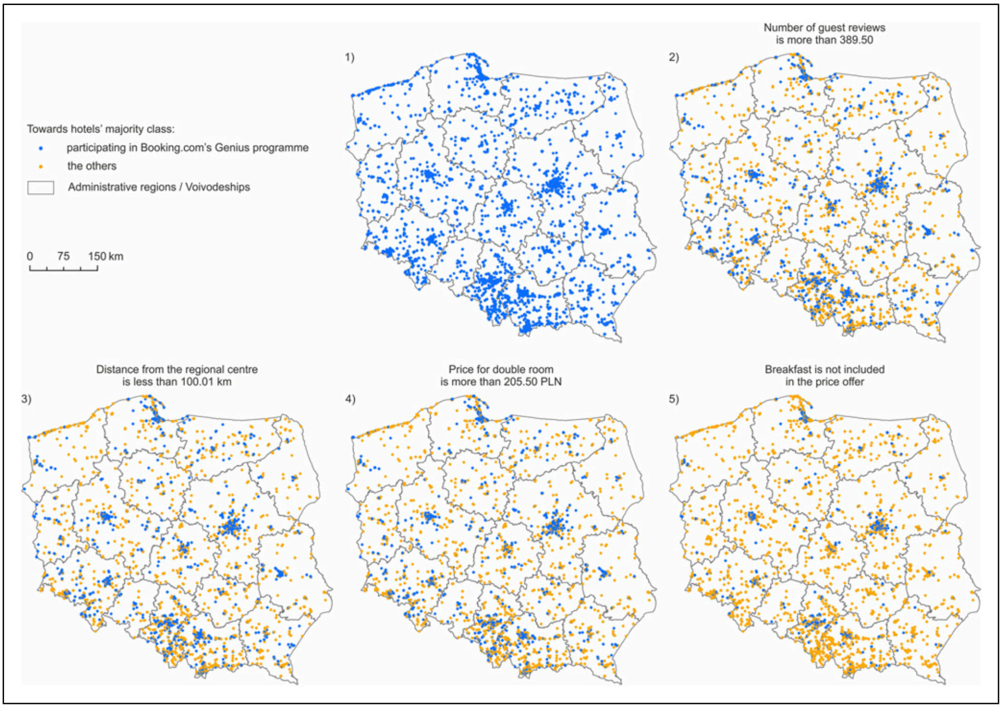

Figure 3. Most efficient spatial pattern to implement the Booking.com's Genius loyalty and marketing programme in Polish hotel facilities. Source: Own elaboration based on data collected from Booking.com using Octoparse.

marketing and loyalty programmes. The application of methods such as the Random Forest Classifier, followed by cartographic analysis, offers a novel approach to examining the factors that shape the adoption of AI-supported tools offered by OTAs.

The study also highlights the asymmetry between traditional hotel-managed marketing and RM tools and platform-provided, AI-supported systems. Although the former are designed to enhance hoteliers' decisions concerning staffing, purchasing, and budgeting (González-Serrano and Talón-Ballestero, 2020; Weatherford and Kimes, 2003), the latter prioritise the strategic and commercial goals of the platform providers – namely, international expansion and profit maximisation (Clemons et al., 1999; Del Romero Renau, 2018; Srnicek, 2019). This misalignment between platform and hotelier priorities adds complexity to existing theoretical debates about power and autonomy in hospitality and contributes to the questions asked at the beginning of our article: "Who adopts AI-supported OTA-led loyalty and marketing tools, and where is this adoption concentrated?"

Furthermore, our study provides a geographical perspective on the dynamics of platform capitalism by demonstrating that adoption of platform-led loyalty tools is concentrated among large, centrally located, and revenue-oriented hotels, rather than among resource-constrained peripheral properties, as commonly assumed. We show that small hotels – particularly those in peripheral areas – are disproportionately disadvantaged in adopting AI-supported marketing and revenue management tools, despite their accessibility via OTAs. Altgough partially aligned with Balk (2024), our findings extend previous research by showing that platform engagement may reflect strategic amplification by resource-rich hotels rather than dependency driven by resource scarcity.

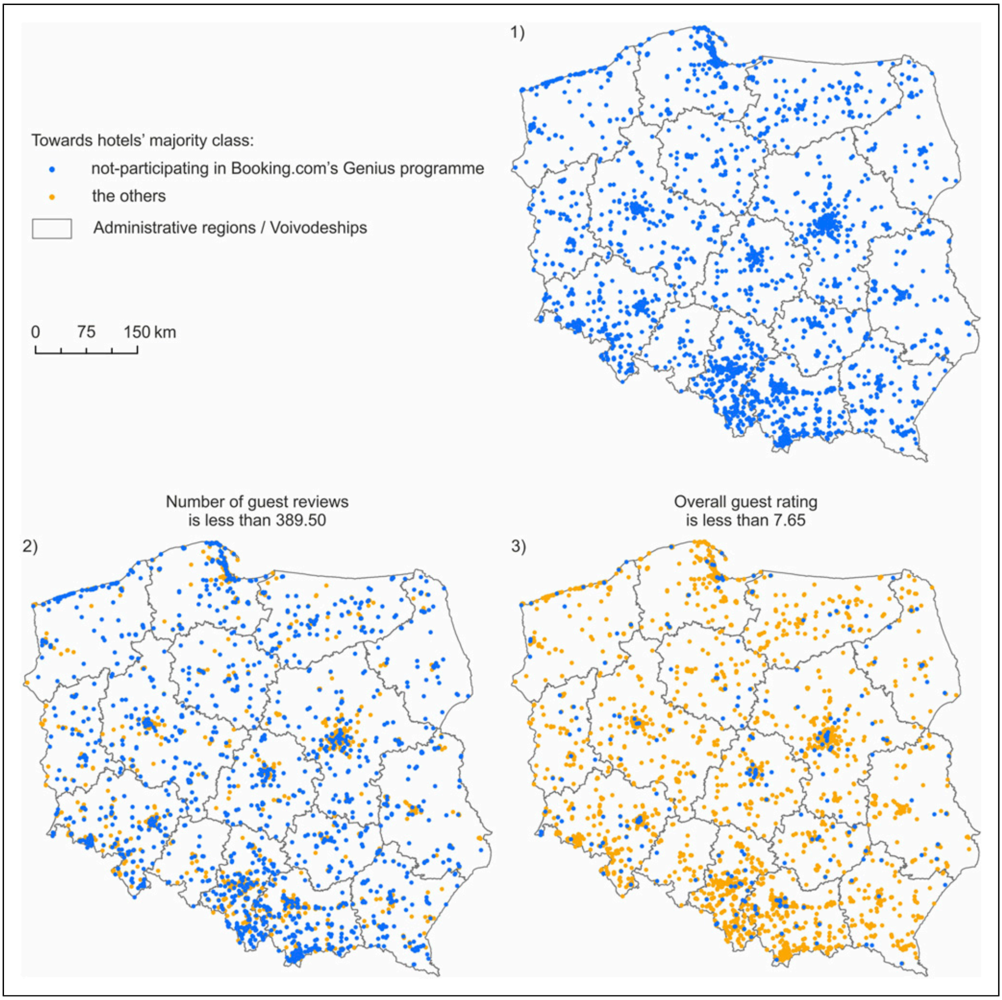

Figure 4. Most efficient spatial pattern to not implement the Booking.com's Genius loyalty and marketing programme in Polish hotel facilities. Source: Own elaboration based on data collected from Booking.com using Octoparse.

Moreover, some rural areas still rely on traditional marketing methods and lack support from big data and AI technologies (Xie and He, 2022).

Our findings contribute to the literature on technological marginalisation and the digital divide between cities and rural peripheries. Even where infrastructural differences between rural and urban areas have diminished, the user-level digital divide remains significant (Janc and Siłka, 2016). Moreover, this digital divide is strongly associated with education and income (Eichhorn et al., 2022).

Practical and social implications

This study provides insights for industry stakeholders, particularly with regard to the impact of AI-supported marketing and RM tools on SMEs and hotels located in disadvantaged or peripheral regions. The findings show that small hotel facilities adopt AI-supported marketing and RM tools provided by OTAs only to a limited extent. Regardless of the technology provider, specific organisational and managerial resources are required for implementation (Atanasova and Ivanov, 2021; Nam et al., 2021; Napierała et al., 2020; Sun et al., 2025). As a result, even relatively accessible OTA-based solutions tend to be adopted by larger, centrally located hotels that target higher price segments, rather than by smaller, lower-priced, and peripheral establishments.

This gap leads to reduced competitiveness (Balsiger et al., 2023; Horváth and Szabó, 2019) and an increased risk of dependency on a single platform for both distribution and pricing strategies (Binesh et al., 2021; Surdez et al., 2024). Larger hotels with more complex management structures and specialised human capital are more likely to use these digital tools effectively. These findings support the need for targeted education and capacity-building initiatives to ensure a greater participation in AI-supported marketing and RM adoption, especially among SMEs (Ivanov and Webster, 2024; Roelofsen, 2024).

AI-based loyalty management, marketing, and RM requires professionals to demonstrate both critical thinking and advanced digital skills. For example, while small price adjustments can be automated, major pricing decisions still require active human oversight (Ivanov, 2024; Ivanov and Webster, 2024). This reinforces the idea that human-AI collaboration remains central to responsible loyalty management, marketing, and RM practice. However, as this study suggests, this capacity is often limited to larger organisations.

The implications extend to government and policy actors. There is a growing need to ensure that AI technologies serve the interests of SMEs and local communities rather than benefit large platforms exclusively (Bettoni et al., 2021; Horváth and Szabó, 2019). Public policy could support the development of locally controlled or nationally supported technologies that provide viable alternatives to globally dominant platforms (Yeşilbağ, 2022). The study echoes calls for differentiated responses: some hoteliers may adopt a defensive stance, relying on state protections, while others embrace platforms proactively as part of a modern business strategy (Surdez et al., 2024).

Zuboff (2019) highlights the profound asymmetries of knowledge and power between platforms and their users, advocating for new forms of social control – including political measures and the collaborative actions of social movements – over technology giants. These responses are likely to vary between regions, as confirmed by the spatial differences observed in this study. Hence, the role of local and regional tourism organisations, as well as the role of hotels within these organisations, should be highlighted in strengthening the capabilities of hotels operating in peripheral areas. Individual hotels lack the market power required to overcome the market structures and tools created and controlled by digital platforms.

Limitations and future research agenda

The primary limitation of this research is its dependence on a single data source: Booking.com. Independent hotels are known to be overrepresented on the platform. Additionally, large and high-category hotels tend to allocate only a small share of their inventory to intermediary channels such as Booking.com (Martin-Fuentes and Mellinas, 2018). This may affect the representativeness of the findings. However, access to information on whether hotels use other AI tools for loyalty management, marketing and RM purposes (such as solutions provided by hotel chains' franchisors or software providers) is strictly limited or, in many cases, unavailable. Hence, relying solely on Booking.com data is justified, especially given that this platform is the largest OTA in Europe, with a 69.3% market share (Walker, 2024).

Another area not explored within the scope of this research is the role of the Booking.com's Genius programme relative to other loyalty management, marketing, and RM practices. It remains unclear whether hoteliers use this tool in isolation or in combination with other strategies involving human oversight. Another limitation of our study is its reliance on pricing data collected for a single booking date and a single check-in date. This approach may not fully capture temporal fluctuations or short-term price shocks. Future research could benefit from a panel-data approach to better account for time-varying pricing and the adoption of platform tools.

The evolving role of generative AI in consumer decision-making warrants further investigation. How tourists use AI to choose destinations and experiences can significantly reshape not only the industry but also its reliance on intermediaries such as OTAs (Booking.com, 2024; Mariani and Dwivedi, 2024). There is a growing need to explore how AI can influence not just loyalty management, marketing, and pricing, but also the spatial organisation of tourism and destinations' tourism policies.

Gursoy and Cai (2025) note that AI can support sustainable development goals, particularly through operational efficiency. However, as our findings confirm, the social and economic sustainability dimensions are often overlooked in AI-supported marketing and RM – especially when implemented by large platforms. The Genius programme exemplifies how AI can support – but not determine – loyalty, marketing, and pricing strategies. However, AI systems must account not only for economic interests, but also for those of employees, local communities, public authorities, and the environment (Napierała and Pawlicz, 2023).

AI-powered marketing and RM tools should be evaluated within the broader context of capitalist growth models and their consequences for both people and the planet. Scholars have proposed alternative uses of AI that prioritise redistributive goals, progressive pricing, disincorporated marketing, or community-based tourism models (Kelleci, 2024; Murray et al., 2023). However, the environmental cost of AI – including energy consumption and emissions – raises questions about the sustainability of the technologies themselves. The distinction between "AI for sustainability" and "sustainable AI" must be acknowledged (Ligozat et al., 2022; Van Wynsberghe, 2021).

A final concern is the question of digital humanism. Future research should investigate human control over AI systems, stakeholder participation in AI-supported decision-making, and the ethical implications of AI use (Inversini, 2025). Roelofsen (2024) highlights the risk of reducing people to data points in technocratic approaches, when they are, in fact, emotional and social actors embedded in physical and virtual spaces. Future studies should address this by incorporating geographical and human-centred perspectives more explicitly. As Zuboff (2019: 76) suggests: "*If the digital future is to be our home, then it is we who must make it so. We will need to know. We will need to decide. We will need to decide who decides. This is our fight for a human future.*"

Following the recommendations of Hall and Cooper (2025), future research could explore the long-term impacts of AI-supported loyalty programmes, marketing activities, and dynamic pricing on all stakeholders in the hotel ecosystem: guests, employees, managers, suppliers, community actors, and local residents – recognising that "there are no guests without hosts". It could also investigate customer satisfaction and behaviour (including loyalty) shaped by AI tools and compare these outcomes with those of traditional marketing and RM methods. In addition, ethical dimensions such as algorithmic transparency and fairness deserve closer scrutiny. Finally, further inquiry is needed into the environmental and social consequences of AI-supported marketing and dynamic pricing: does it encourage overconsumption in high-demand areas or contribute to exclusionary pricing? Alternatively, could AI serve as a tool for promoting more equitable and sustainable tourism?

Conclusions

Our study contributes to the discussion on how platform capitalism influences the lodging market, with a particular focus on loyalty management, marketing, and pricing within lodging services. The research used data on the willingness of Polish hoteliers' to participate in the Booking.com's loyalty and marketing programme in 2024, alongside related site-specific and situational factors. A Random Forest Classifier algorithm, complemented by cartographic analysis, was used to achieve the objective of the study: to identify key feature-based influences and associated spatial patterns in the adoption of AI-supported marketing and RM technology provided by OTAs for hotel facilities.

The findings indicate that site-specific and situational factors significantly influence the variability in hoteliers' willingness to adopt AI-supported tools offered by OTAs. Large hotels located in the cores of metropolitan areas or in the centres of popular mountain destinations, offering higher-priced services and demonstrating greater awareness and understanding of RM, are the most likely to adopt these advanced tools. AI-supported technology primarily targets revenue-focused entities. In contrast, small and low-rated hotels do not use the Genius loyalty and marketing programme of Booking.com, as they appear to lack the capacity to implement AI-supported marketing and RM tools, even when conveniently provided by OTAs. This outcome has significant negative implications for revenue distribution in disadvantaged and peripheral areas.

Our findings highlight the critical importance of market positioning, operational knowledge, and geographic location in determining the adoption of AI-powered marketing and RM solutions within the lodging sector.

Acknowledgements

We would like to acknowledge the support of Maciej Adamiak (University of Lodz, Poland) for his contributions to the initial discussions that shaped the research concept, including geographical analysis, as well as for programming the Random Forest Classifier. We are also grateful to Katarzyna Leśniewska-Napierała (University of Lodz, Poland) for her assistance in generating maps using GIS software.

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Ethical considerations

This article does not contain any studies with human or animal participants.

Consent to participate

Therefore, informed consent is not required.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability Statement

The data supporting the findings of this study were obtained through scraping a small portion of content from Booking.com's platform using Octoparse solutions. Booking.com's Customer Terms of Service, Section A14.2, prohibit scraping for commercial purposes. While scraping limited data for research or educational purposes may qualify as fair use, restrictions apply under Booking.com's Customer Terms of Service, Section A14.1. Consequently, the data are not publicly available. However, data are available from the authors upon reasonable request for research or educational purposes.

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