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Review article

WHEN ALGORITHMS DISCRIMINATE: AI BIAS AND ITS IMPLICATIONS FOR TOURISM AND HOSPITALITY

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ABSTRACT

This paper analyses the problem of bias in artificial intelligence (AI) systems from the perspective of the tourism industry. Through a typical scenario of a tourist experience, it considers the different manifestations of AI bias and analyses a conceptual framework for understanding its implications. The basic approach is grounded in a narrative literature review that synthesises a spectrum of studies on bias and consumer experiences in tourism. The paper anticipates the impact of bias in AI systems on the tourist experience in the pre-trip, on-site, and post-trip phases, considering both the perspective of tourists and that of service providers. It is emphasized that most biases originate from the use of AI on online platforms, which influences information search and tourist decisions, but also shapes the marketing operations of service providers. The conclusion considers broader societal impacts, governance implications, and effects on technology.

Keywords: *artificial intelligence; bias; tourism; tourist experience.*

INTRODUCTION

Artificial intelligence represents the ability of computer systems to perform complex tasks that require human intelligence, such as logical reasoning, learning from external data, and independent problem solving (Haenlein & Kaplan, 2019; Morandín-Ahuerma, 2022). As a scientific discipline, it develops algorithms and theories that enable machines to flexibly adapt to their environment and achieve goals with various levels of autonomy (Wang, 2019). In a broader sense, these systems simulate cognitive functions through processes of perception and action, striving to functionally imitate the way humans think and act (Chumakov, 2025; Garg, 2021).

Thanks to its ability to recognize and enhance both implicit and explicit real-world phenomena, AI is increasingly used in the tourism and hotel industry (Tussyadiah, 2020), primarily for task automation (Berezina et al., 2019), robotization (Blöcher & Alt, 2020), in marketing and sales, finance (Millauer & Vellekoop, 2019), and increasingly in customer interaction (Libai et al., 2020). AI has proven effective in predicting hotel prices and booking cancellations, enabling market segmentation, increasing visitor satisfaction, and creating value for tourists and businesses (Sun et al., 2019; Stankov et al., 2025).

Despite the numerous benefits, the application of AI has opened up specific challenges (Vujičić et al., 2024; Solarević et al., 2025). Contemporary applications have prompted ethical debates in science, in organi-

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zations, and among consumers and policy makers, which has launched a movement for "ethical AI" (Gretzel & Stankov, 2021). The most frequent concerns relate to transparency, accountability, and data quality, which have led to growing interest in so-called "explainable AI", that is, the ability of systems to generate outputs that are understandable to humans (Meske et al., 2020). Numerous initiatives for the responsible development of AI have emerged, resulting in increased regulation and comprehensive policies (e.g., High-Level Expert Group on Artificial Intelligence 2019; Université de Montréal, 2017). The Montreal Declaration (2017) states that the development and use of artificial intelligence systems must enable the growth of well-being and calls for applications that contribute to a fair society without discrimination. All these initiatives seek to maximize the benefits of AI while reducing risks and harms (Thiebes et al., 2020).

One of the key areas of risk is bias in AI, defined as unfair discrimination against individuals or groups at the expense of others (Friedman & Nissenbaum, 1996). In other words, AI bias represents a systematic and unfair error in the decision-making process that results in worse treatment or unfavourable outcomes for certain individuals or demographic groups (Ferrara, 2024; Yang et al., 2024). This phenomenon manifests itself as the model's tendency to favour one group over another, thereby violating the principle of equality, which implies the absence of prejudice (González-Sendino et al., 2023; Pessach & Shmueli, 2022). The sources of such bias are multiple: from unbalanced and historically discriminatory data, through the design of algorithms themselves which may amplify existing inequalities, to the subjective influences of designers and the very context in which the system is applied (Mehrabi et al., 2021; Ntoutsi et al., 2020; Gray et al., 2024). In essence, when an AI system is biased, it consistently deviates from a fair decision because of the way it has been trained, designed, or used in practice (Varsha, 2023).

Examples of biased algorithms are increasingly being reported in the media and analysed from technological, ethical, legal, and business perspectives (Bostrom & Yudkowsky, 2014). However, research in tourism mostly emphasizes the positive effects of AI, while negative consequences remain poorly investigated. Since tourism is highly dependent on information and since products and services cannot be tried before purchase, trust is extremely important. The increased role of AI and the expansion of digital platforms introduce an additional intermediary in the relationship between supply and demand (Ågerfalk, 2020). Unethical or unfair treatment, arising from biased algorithms, can undermine trust, with various consequences for all stakeholders (Hohenstein & Jung, 2020).

Building on the research of Kalinić and colleagues (2026), this paper applies the method of a narrative literature review in order to assess and synthesize a wide range of studies on AI bias and consumer experiences, particularly in the context of smart destinations. The paper does not represent an exhaustive review of the existing literature but conceptualizes this issue in the specific setting of tourism and hospitality. The chosen method allows a comprehensive insight into the manifestations of bias and its importance in the broader tourism discourse.

More specifically, the relevant literature was identified through searches of the Scopus, Web of Science, and Google Scholar databases, complemented by snowball sampling of the reference lists of key publications. The search combined terms related to artificial intelligence and bias (e.g., "AI bias", "algorithmic bias", "algorithmic fairness", "algorithmic discrimination") with terms related to the tourism and hospitality domain (e.g., "tourism", "hospitality", "tourist experience", "smart tourism", "online travel platforms", "recommender systems"). Sources were included when they conceptualised, demonstrated, or empirically examined bias, fairness, or discrimination in AI systems and were relevant to at least one phase of the tourist experience (pre-trip, on-site, or post-trip) or to tourism service providers; purely technical contributions without a clear link to consumer or service contexts were excluded. Because the development and deployment of AI advances faster than the publication cycle of peer-reviewed research, a limited number of illustrative examples were drawn from reputable news outlets and industry portals (e.g., Fung, 2019); Nikolić, 2019; Hays, 2021; Lomas, 2021). These sources are used solely to document real-world manifestations of bias that have not yet been captured in the academic literature, whereas the conceptual claims of the paper remain grounded in peer-reviewed studies.

THE NATURE OF AI BIAS

The perception of bias in AI depends on the definition of fairness, which varies depending on context and purpose. Bias relates to fairness and the distribution of resources (Floridi et al., 2018) but may also have a representational dimension (Barocas & Selbst, 2016). Most current AI systems are based on machine learning, particularly on deep learning methods (Thiebes et al., 2020; Mehrabi et al., 2021). The development of such systems involves three main phases: data input, modelling, and output. Bias can arise in any of these phases. The first step in training a model includes collecting large amounts of data from various sources and in different formats. Bias can arise from sampling errors, poor data quality, or because the data already reflect societal biases. In the second phase, programmers design algorithms and models. Personal biases or inadequate assumptions can be encoded into the algorithm and thereby create an unfair model. In the third phase, bias arises from the way users interact with the outputs of the algorithm. User feedback is used to improve existing models or to train new ones. If the interactions are biased, they can create a dangerous feedback loop that amplifies the bias and makes it harder to recognize and isolate (Kalinić et al., 2026).

CONCEPTUALIZING THE IMPACT OF AI BIAS IN TOURISM

Tourists use many AI-based platforms throughout all phases of travel (Stankov & Gretzel, 2020). Machine algorithms evaluate tourists when they search for information, check into accommodation, try to reach the airport as quickly as possible, and after the trip when they summarize their impressions. A distinction is drawn between manifest and latent bias. Manifest bias occurs when a user recognizes the error, even without consciously linking it to the algorithm; for example, when one notices that others receive different recommendations with the same input data. Latent bias remains unnoticed and creates feedback loops that may amplify negative effects eventually (Kalinić et al., 2026).

Figure 1 summarizes this conceptualisation, linking the sources and types of AI bias to their manifestations across the three phases of the tourist journey and to their consequences for tourists and service providers, including the feedback loop through which latent bias accumulates and returns to earlier phases.

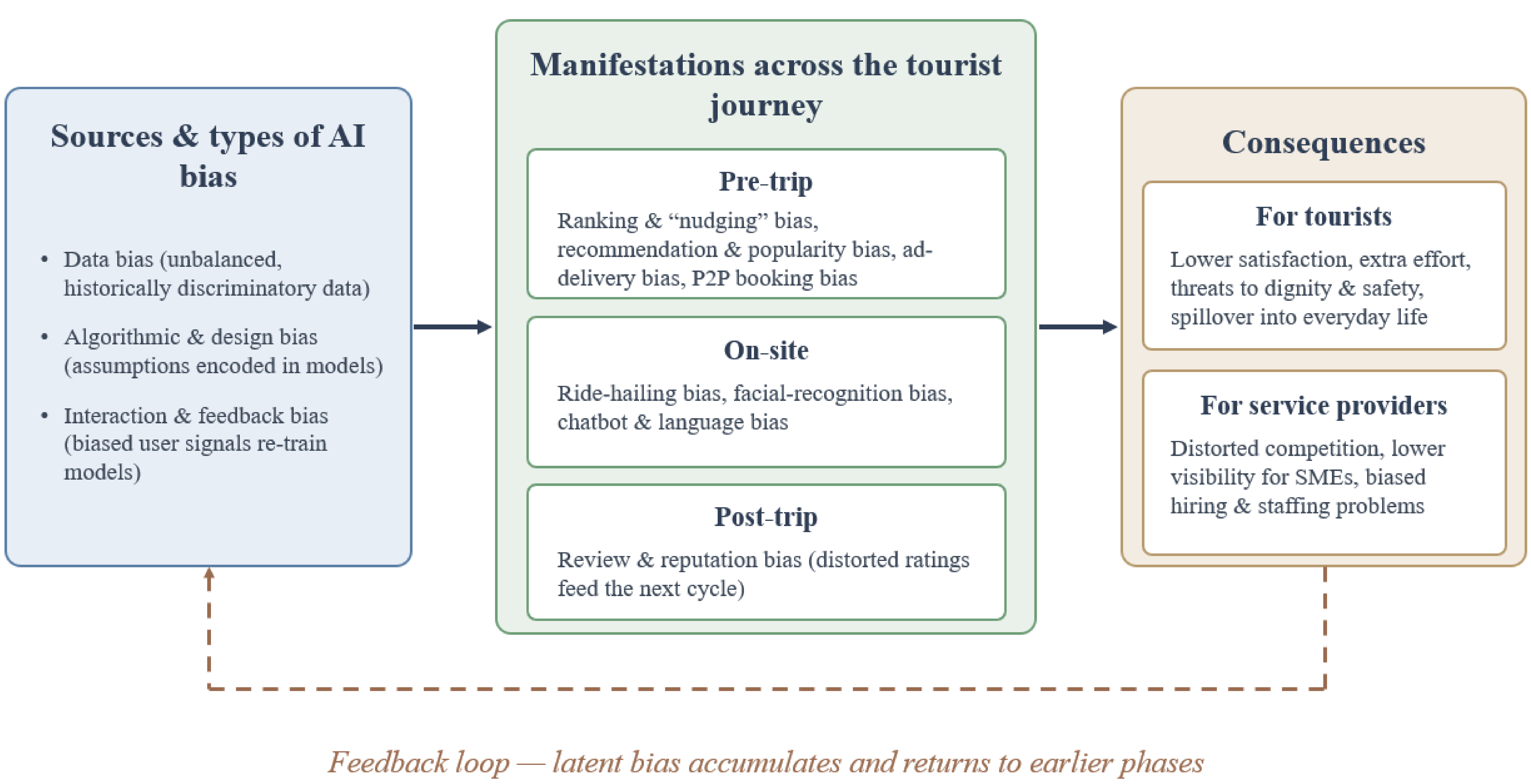

Figure 1. A conceptual model of AI bias in tourism

Before the trip, tourists usually search for information using online booking and sales platforms. To increase engagement and revenue, platforms apply "nudging" techniques (Schneider et al., 2020). Research shows that some platforms apply practices that steer users toward more expensive options (Hannák et al., 2014). Although segmentation is not illegal, algorithmic biased ranking or recommendations can mislead users about the availability or popularity of offers (S. S. Fung et al., 2019) and discriminate against them on the basis of demographic characteristics (for example, gender or ethnicity).

Platforms also use systems for recommending relevant content to users (Lambrecht & Tucker, 2019). At the same time, popularity bias may appear that favours popular offerings regardless of quality (Mehrabi et al., 2021), or presentation bias, since users can only click on what is shown to them, which narrows the spectrum of choice (Bozdag, 2013). Personalization can lead to filter bubbles, that is, isolated information environments in which information is tailored to the extent that the diversity of content is lost (Nguyen et al., 2014).

Information search is not always oriented toward functional goals since tourists often gather information from the experiences of others. In such situations, biased ad-delivery algorithms can lead to discrimination, e.g., certain groups may have more or fewer opportunities to see particular ads (Ali et al., 2019).

Accommodation-sharing platforms, such as Airbnb, allow hosts to accept or reject reservations. Edelman et al. (2017) found that guests with African American names have a 16% lower chance of being accepted. Although this is a societal bias, the algorithm-based design of the platform enables its existence and amplification.

During the trip and during the stay at a destination, tourists often continue to look for information about tours and other services. The study by Ge et al. (2016) showed that some users wait longer and experience more frequent cancellations on the basis of ethnicity, and that women are driven longer routes and pay more. An even greater risk comes from the use of facial recognition systems at airports and in shopping malls (Nikolić, 2019; Belk, 2020). These systems show weaknesses in recognizing people from underrepresented groups (B. Fung, 2019) or lead to misidentification and detention (O'Neil, 2018).

Chatbots and personal assistants are present in more and more phases of service delivery. Chatbots are trained on huge text datasets and absorb the stereotypes and biases present in language (Fisk et al., 2018). They can reproduce and deepen gender, ethnic, and cultural prejudices, leading to inadequate support for tourists from different linguistic and cultural backgrounds or with disabilities.

After the trip, tourists often share their experiences and leave reviews. These ratings do not always reflect the real experience (Rouliez et al., 2019). In this way an additional bias arises, which can lead to a distorted perception of service quality. These reviews serve future tourists, but also as data for fine-tuning algorithms, creating a bias loop that returns to the pre-trip phase.

THE IMPACT OF BIAS IN ARTIFICIAL INTELLIGENCE SYSTEMS ON SERVICE PROVIDERS

In order to make decisions, service providers in tourism often use large amounts of data collected through interactions with tourists on online platforms. Platforms rely on ranking and recommendation algorithms in order to personalize content (Bozdag, 2013).

On the supply side, the effects of bias are twofold: they affect tourists, but also business actors themselves. For example, popularity bias may favour popular destinations or hotels, creating inequality that does not reflect real competition (Cimbaljević et al., 2019; Gajdošík, 2018). Popularity may depend on the design of the algorithm; research suggests that platforms sometimes favour hotels with more lucrative contracts (Riemer & Lehrke, 2009) or automatically discriminate against certain content followers (Hays, 2021). In some cases, algorithms make no distinction between justified employee absences and lateness, and unfairly penalize workers (Lomas, 2021).

Biased ad delivery also affects service providers. Ali et al. (2019) established that Facebook's ad-delivery algorithm produces outcomes contrary to advertisers' intentions. Filters often favour businesses with larger advertising budgets, reducing the visibility of smaller actors and increasing the risk of reputational damage due to inappropriate content. The same algorithms are also used for ads aimed at potential employees: women more often see more expensive consumer ads, while less attention is given to them in job ads, which creates prejudice in hiring (Lambrecht & Tucker, 2019). If an algorithm that evaluates candidates learns from data that reflect gender differences, the bias is further amplified (O'Neil, 2018), deepening inequalities and leading to staffing problems.

In the post-trip phase, reviews are the main source of bias that affects businesses. Digital platforms allow users to rate transactions and give opinions; this is where societal biases and preferences are transferred. In addition, dissatisfied customers are more likely not to leave a review, which distorts the reputation system (Fradkin et al., 2015; Tadelis, 2016). These biases can confuse managers in their decision-making and misinform tactical or strategic planning (Rouliez et al., 2019). Since platforms use these data to train recommendation and search algorithms, biased data can further amplify discrimination and create unfair competition (Zervas et al., 2021).

EFFECTS OF BIAS IN ARTIFICIAL INTELLIGENCE SYSTEMS ON THE TOURIST EXPERIENCE

Although contemporary tourist experiences are increasingly dependent on AI, the human experience remains at the centre. Unfair treatment due to bias can damage the experience, reduce satisfaction, and cause harm (Stankov & Gretzel, 2020; Kovačić et al., 2024). The consequences range from minor problems in service delivery, through distraction, to serious harm. In milder cases, bias causes disturbances; for example, a tourist may be inconvenienced because of biased search results. However, if the benefits outweigh the negative effects, tourists are likely to continue using the platform, accepting the trade-off.

Bias can also affect those who are not its direct targets. Even if not a direct victim of discrimination, an observer may feel negatively because of injustice toward others (Mattila et al., 2014). In the case of prejudice, tourists may be forced to invest additional effort in order to achieve the desired experience (Buhalis et al., 2019). In more serious cases, bias can prevent the goal of interaction with the digital system from being achieved, for example, a complicated chatbot that makes it difficult to complete a task.

In the most extreme circumstances, biased algorithms can endanger the health and well-being of tourists (Raji & Fried, 2021). The greatest concern relates to facial-recognition systems, which can cause physical dangers or violations of dignity (High-Level Expert Group on Artificial Intelligence 2019; Stolton, 2020).

Bias is difficult to detect, since some injustices can easily be identified (e.g., denial of service), while others remain hidden (e.g., the absence of an ad due to a discriminatory algorithm). Manifest biases can be mitigated through timely intervention; latent ones are more dangerous because they generate feedback loops. Given the complexity of the sources and consequences of bias, mitigation strategies are needed. In cases of distraction or unwanted discrimination, service providers can inform clients in advance or offer compensation; but this entails costs and burdens staff-to-guest relationships.

The development of AI requires highly qualified personnel and significant resources for data processing. Since most tourism businesses belong to small and medium-sized enterprises, most of the development is carried out by technology companies. As a result, service providers find themselves in a position similar to that of tourists and can only react to the consequences of bias, while responsibility for the algorithm rests with the developers. Although tools for assessing the fairness of algorithms have emerged, it is crucial that tourists and providers understand the limitations and potential of algorithms and know when and how to use them. Developers must ensure transparency and training about possible biases, while policy makers should set regulatory frameworks that prevent harm and discrimination.

Table 1 synthesises the preceding discussion by mapping the main types of AI bias to their touristic context and to their consequences for tourists and for service providers.

Table 1. Types of AI bias across the tourist journey and their consequences for tourists and for service providers.

Type of bias	**Touristic context**	**Consequences for tourists**	**Consequences for service providers**
Ranking & “nudging” bias	Pre-trip: online booking and search platforms	Steered toward more expensive options; misled about the availability or popularity of offers	Distorted competition; reduced control over how offers are surfaced
Recommendation & popularity bias	Pre-trip / on-site: recommender systems	Narrowed choice (presentation bias); filter bubbles and loss of content diversity	Popular destinations and hotels favoured regardless of quality; inequality among providers
Ad-delivery bias	Pre-trip: targeted advertising	Discriminatory exposure to ads (e.g., by gender or ethnicity)	Outcomes contrary to advertisers’ intentions; lower reach for smaller budgets; reputational risk
Accommodation-platform bias	Pre-trip: peer-to-peer booking (e.g., Airbnb)	Lower acceptance for guests with minority-associated names	Amplification of societal discrimination; reputational and legal exposure
Ride-hailing & local-service bias	On-site: transport and local services	Longer waits, more cancellations, longer routes and higher fares by ethnicity or gender	Liability and erosion of trust in the service ecosystem
Facial-recognition bias	On-site: airports, malls, security checks	Misidentification, detention; threats to dignity and physical safety	Legal and ethical liability; regulatory scrutiny
Chatbot & language bias	On-site: customer-service assistants	Inadequate support for users of different languages or cultures, or with disabilities	Service failures and brand damage
Review & reputation bias	Post-trip: rating and review systems	Distorted perception of service quality	Misinformed managerial decisions; biased data fed back into the recommendation loop
Hiring-algorithm bias	Cross-cutting: workforce and recruitment	Indirect effects through reduced service quality	Discriminatory hiring; staffing problems; deepened inequalities

SPILLOVER OF HARM CAUSED BY BIAS IN AI SYSTEMS INTO EVERYDAY LIFE

Tourism is oriented toward improving physical and mental well-being, so negative experiences related to AI may also disrupt tourists’ everyday life. Bias may incorrectly attribute certain characteristics to tourists or place them into certain groups; for some vulnerable or underrepresented groups, this may cause a feeling of alienation. If tourists are a minority on a platform, bias may reduce the usefulness of AI. Since tourism is global, biases may have different impacts depending on the cultural context and the digital literacy of users (Abid et al., 2021). If AI bias is not clearly explained, distrust may deepen (Hohenstein & Jung, 2020), encouraging avoidance of technology and the development of “defensive” strategies (Stankov & Gretzel, 2021). In this way, many of the benefits of tourism are erased: authenticity, well-being, and humane values. Consequences include dehumanization, technostress, and even violations of human rights (Stankov & Gretzel, 2020).

THE RELATIONSHIP BETWEEN BIAS IN AI SYSTEMS AND DATA PRIVACY

The mechanisms that generate the biases discussed above, the collection and processing of large volumes of behavioural and personal data across every phase of the tourist journey, are also the source of a closely related risk: threats to data privacy. The two concerns are intertwined, since the same data pipelines that can encode discrimination also expose tourists to surveillance and misuse, and both ultimately bear on the trust on which tourism depends.

Beyond bias, data privacy represents a key concern in the use of AI. AI systems rely on large amounts of sensitive data, which increases the risk of information leakage, unauthorized surveillance, and misuse. Privacy violations linked to AI have been recorded in various contexts, indicating the consequences of insufficient protective measures and a lack of transparency. Laws and regulations such as the General Data Protection Regulation (GDPR) emphasize the protection of privacy and data security, requiring compliance in order to prevent harm (Ijaiya, 2024).

To mitigate these risks, innovative technological and ethical strategies are being developed. New privacy-preserving machine learning methods enable AI models to process data without exposing individual sensitive information, balancing utility with protection (Ijaiya, 2024).

Explainable AI models foster transparency, helping stakeholders to understand AI decisions and increasing accountability, which is crucial for combating bias and privacy risks (Ijaiya, 2024). In addition, conducting cybersecurity risk assessments tailored to AI environments is essential for preventing breaches and insider threats, especially in sensitive sectors such as finance (Salami et al., 2025).

In the tourism context, therefore, mitigating bias and protecting privacy are complementary requirements rather than separate problems: both are necessary to preserve tourists' trust and the well-being that tourism is meant to foster.

CONCLUSION

This paper synthesised a dispersed body of literature into a single, phase-based conceptualisation of AI bias in tourism and hospitality. The main findings are threefold. First, AI bias is not confined to a single touchpoint but recurs throughout the tourist journey, from biased ranking, recommendation, and ad-delivery systems in the pre-trip phase, through discriminatory ride-hailing and facial-recognition systems on site, to distorted review and reputation systems after the trip, and these stages are linked by feedback loops that allow latent bias to accumulate. Second, the consequences are twofold, affecting tourists (reduced satisfaction, additional effort, and, in extreme cases, threats to dignity and safety) and service providers (distorted competition, reduced visibility for smaller actors, and biased hiring), while responsibility largely rests with the technology developers rather than with tourism businesses, most of which are small and medium-sized enterprises. Third, these harms can spill over into tourists' everyday lives and are compounded by data-privacy risks that arise from the same data pipelines.

The principal contribution of this paper is therefore conceptual rather than empirical. Unlike the bulk of prior tourism research, which has predominantly emphasized the benefits of AI and has treated bias only in passing, this study offers an integrative, tourist-journey framework that organizes the manifestations and consequences of AI bias for both tourists and providers and situates them within the broader discourse on digital well-being and ethical AI in tourism. In doing so, it extends the conceptual work of Kalinić et al. (2026) from the smart-tourism domain to the full tourist experience and provides a structured agenda for the future empirical research outlined below.

Tourists possess different levels of awareness and expertise regarding AI technologies (Stankov et al., 2024). This raises theoretical questions about how cognitive and perceptual differences affect the recognition of unfair treatment. Existing research and privacy policies emphasize that transparency is crucial for informed decision-making (Wu et al., 2012). However, theoretical models point to a tension between users' desire to understand "why" an algorithm operates the way it does and their willingness to use it when explanations emphasize procedure rather than motives. In contexts where AI mediates the interaction, consumers tend to attribute discrimination to the algorithm itself (Hohenstein & Jung, 2020). Theories of consumer behaviour distinguish segmentation from personalised pricing; therefore, models of responsibility allocation must be adapted to scenarios in which the "other side" is an algorithmic service provider rather than a human being.

The tourism sector operates in different cultural environments, so fairness frameworks must take into account differences in norms. Existing theories of moral reasoning may not capture how culture shapes the perception of fairness in a digital environment; theories need to be extended to AI-mediated interactions.

From a managerial and marketing perspective, the impact of bias remains insufficiently explored. Practitioners need empirical research on how biased algorithms affect brands and marketing performance (Stankov et al., 2022). Many negative experiences arise from participation in online marketplaces that are inherently biased. Managers should be aware of how these systems affect visibility, market entry, and pricing strategies; empirical studies can help in developing guidelines for fair competition. Since human contacts in hospitality are crucial, organizations should investigate how bias affects employment.

Differences in legal frameworks further complicate practice. Global service providers often implement the same systems in different legal contexts. Managers must understand local regulations and develop protocols for handling complaints in international situations.

Although AI in tourism is often perceived as less risky than its application in healthcare or finance, implicit use can lead tourists to unconditionally trust automated decisions, exposing them to injustices. The tourism industry should develop guidelines for transparency and user education; tourists must know when algorithmic decisions affect their experience and how to report injustice.

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