Research-Thesis: How does AI transparency influence purchase intention in online tourism platforms?

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How does AI transparency influence purchase intention in online tourism platforms?

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Abbreviation	*Full form*
AC	Attention Check
AI	Artificial Intelligence
AIL	AI Literacy (scale items AIL1–AIL4)
AIT	AI Transparency (scale items AIT1–AIT3)
BCN	Barcelona–El Prat Airport (IATA code)
BRU	Brussels Airport (IATA code)
CC	Comprehension Check
Cond.	Condition (used in tables: Cond. A, Cond. B)
CT	Consumer Trust (scale items CT1–CT5)
FP	Fairness Perception (scale items FP1–FP5)
H1–H5	Research Hypotheses 1 through 5
IATA	International Air Transport Association
JASP	Statistical analysis software used for hypothesis testing
MAILS	Meta AI Literacy Scale (Carolus et al., 2023)
MC	Manipulation Check (items MC1–MC2)
ML	Maximum Likelihood
PI	Purchase Intention (scale items PI1–PI4)
SEM	Structural Equation Modeling

Glossary

Term	*Definition*	*Source*
Algorithmic dynamic pricing	The practice of adjusting prices in real time using automated systems based on demand, user behavior and contextual factors.	Spann et al. (2025)
AI transparency	The degree to which the functioning, inputs and decision-making logic of an AI system are accessible and understandable to its users.	Haresamudram et al. (2023)
Fairness perception	A consumer's subjective evaluation of whether a pricing process is transparent, consistent and justifiable.	Xia et al. (2004); Colquitt (2001)
Consumer trust	A consumer's confidence that the platform will behave honestly, competently and in a manner that serves their interests.	McKnight et al. (2002)
Purchase intention	A consumer's self-reported readiness to complete a transaction in a given context.	Pavlou (2003)
AI literacy	A set of competencies enabling individuals to use, understand, detect and critically evaluate AI systems.	Carolus et al. (2023)
Black box	A system that generates outputs without exposing its internal reasoning to those it affects.	Basal et al. (2024)

Causability	The degree to which an algorithmic explanation is understandable to the receiver, determining whether transparency translates into meaningful comprehension.	Shin (2021)
Distributive fairness	The perceived equity of a price outcome, i.e., whether the price charged seems reasonable compared to what others pay.	Xia et al. (2004)
Dual entitlement	The principle that consumers believe they are entitled to a reference price while firms are entitled to a reference profit.	Kahneman et al. (1986)
Ecological validity	The extent to which experimental findings reflect how individuals would behave in real-world settings.	Shadish et al. (2002)
Explainability	The capacity of an AI system to communicate the reasoning behind its outputs in a manner comprehensible to non-expert users.	Haresamudram et al. (2023)
Indirect-only mediation	A mediation pattern in which the independent variable influences the outcome entirely through mediators, with no significant direct effect.	Zhao et al. (2010)
Price personalization	The practice of displaying different prices to different consumers for the same product, based on individual data such as browsing behavior or purchase history.	Priester et al. (2020)
Procedural justice	The perceived fairness of the process through which a decision is made, independently of the outcome itself.	Colquitt (2001); Lind & Tyler (1988)
Reference price	A benchmark price that consumers use to evaluate whether an observed price is fair, based on experience, social comparison or market norms.	Kahneman et al. (1986)
Yield management	A traditional pricing strategy in the tourism industry that adjusts prices based on anticipated demand and inventory constraints.	Kimes (2002)
Informational justification	The act of explaining the reasoning behind a pricing decision, identified as the primary mechanism through which transparency affects consumer evaluations.	Vomberg et al. (2025); De Lucas López et al. (2026)
Interaction transparency	The clarity and quality of information communicated to the user during their interaction with an AI system, as opposed to algorithmic or social transparency.	Haresamudram et al. (2023)
Trusting beliefs / Trusting intentions	Two interrelated dimensions of online trust: trusting beliefs capture whether consumers view the platform as honest and competent, while trusting intentions reflect their readiness to engage with and depend on it.	McKnight et al. (2002)
Heuristic processing	A mode of information processing in which individuals rely on simple cognitive shortcuts rather than systematic evaluation, particularly when they lack the resources to elaborate on incoming information.	Chaiken (1980)
Algorithm appreciation	Attitudinal dispositions reflecting consumers' general tendency to favor or resist algorithmic guidance in decision-making.	Rainy & Dhanekula (2025)

1 Introduction

"Algorithms are opinions embedded in code" (O'Neil, 2016). Every time a consumer searches for a flight or a hotel room on an online booking platform, the price displayed has already been determined by an algorithm. The online travel market was valued at over 640 billion U.S. dollars in 2024 with online bookings accounting for approximately 70 percent of total tourism revenue (Statista, 2024). On platforms such as Booking.com, Expedia and Airbnb, artificial intelligence (AI) continuously adjusts prices in real time based on demand, booking timing, seasonality and user behavior (Kopalle et al., 2023; Spann et al., 2025). Yet despite this omnipresence, recent industry research shows that only 22 percent of consumers report having a good understanding of how AI works even though they interact with it on a daily basis (EY, 2024). In other words, consumers are constantly exposed to algorithmic decisions without understanding how these decisions are made.

This situation creates tension between business optimization and consumer perception. While algorithmic dynamic pricing helps platforms maximize revenue (Spann et al., 2025), it also raises concerns among consumers. A 2024 CivicScience survey found that 68 percent of consumers associate dynamic pricing with "price gouging" (i.e., the practice of charging excessively high prices by exploiting high demand or limited alternatives) and a Consumer Reports survey from the same year showed that 47 percent of Americans strongly oppose personalized pricing (Consumer Reports, 2024). Prices can change between two visits to the same page or differ between two users searching for the same room whereas the logic behind these variations is rarely explained. This opacity generates suspicion and perceptions of unfairness, particularly when consumers feel they may be paying more than others for the same service without knowing why (Vomberg et al., 2025; Xia et al., 2004). The question of whether and how platforms should explain their pricing processes has therefore become central, both for academic research and for regulators. The European Union's Artificial Intelligence Act, the first comprehensive legal framework on AI worldwide, has progressively entered into force since 2024. It explicitly imposes transparency obligations on providers of AI systems, requiring that users be informed when they interact with such systems and that the logic underlying algorithmic decisions be made accessible (European Commission, 2024).

The existing literature has examined these constructs separately. Research on price fairness, which constitutes the theoretical foundation of fairness perception in pricing contexts, has shown that consumers evaluate not only the price itself but also the process through which it was determined (Xia et al., 2004; Colquitt, 2001). Studies on consumer trust in e-commerce have established that trust is a key driver of purchase intention in uncertain online environments (McKnight et al., 2002). More recently, research on AI transparency has demonstrated that providing explanations for algorithmic decisions can restore trust when expectations are violated (Kizilcec, 2016). However, these bodies of literature have largely developed in parallel. Recent reviews of the field (Chenavaz & Dimitrov, 2025; De Lucas López et al., 2026) explicitly note this lack of integration, observing that AI transparency, fairness perception and consumer trust have only recently begun to be considered jointly in algorithmic pricing research. Few studies have integrated AI transparency, fairness perception, consumer trust and purchase intention into a single framework, and even fewer have empirically tested the complete sequential mechanism through which these four constructs interact. This gap is even more pronounced in the context of online tourism, where the intangibility of services and the irreversibility of bookings make consumer trust and fairness perception particularly important (Hamcerencu, 2025; Basal et al., 2024).

This thesis aims to address this gap by answering the following research question: *How does AI transparency influence purchase intention in online tourism platforms?* More specifically, it examines this question through the lens of algorithmic dynamic pricing, investigating the sequential role of fairness perception and consumer trust in the relationship between AI transparency and purchase intention in online tourism platforms. The conceptual model proposes that AI transparency first enhances consumers' fairness evaluations of the pricing process (H1) which in turn strengthens their trust in the platform (H2) and that this trust then drives purchase intention (H3). The full sequential mediation of fairness perception and consumer trust between AI transparency and purchase intention is also tested (H4). Finally, AI literacy is examined as a potential moderator of the relationship between AI transparency and fairness perception based on the expectation that consumers with greater knowledge of AI may process transparency information differently (H5).

The theoretical framework integrates insights from procedural justice theory (Colquitt, 2001; Lind & Tyler, 1988), the price fairness literature (Xia et al., 2004; Kahneman et al., 1986), trust formation theory in e-commerce (McKnight et al., 2002) and research on AI transparency and explainability (Kizilcec, 2016; Haresamudram et al., 2023).

To test these hypotheses, a scenario-based experimental study was conducted. Participants were randomly assigned to one of two conditions (low or high AI transparency) on a simulated and neutral online flight booking platform called 'FlyNow'. All other elements of the scenario remained identical, allowing the study to isolate the causal effect of transparency on fairness perception, consumer trust and purchase intention. The questionnaire was administered through LimeSurvey and combined validated Likert-scale items drawn from established scales for each construct, alongside manipulation checks to ensure that the AI transparency conditions were perceived as intended.

The structure of this thesis reflects the progression of the inquiry itself. It opens with a literature review which develops the theoretical foundations of each construct and formulates the research hypotheses. Building on these foundations, the research design chapter then details the experimental methodology, the sample and the measurement instruments. The empirical findings are reported in the results chapter before being interpreted in the discussion, which situates them within the existing literature and addresses the study's contributions and limitations. The thesis closes with a conclusion summarizing the key findings and outlining their theoretical and managerial implications.

2 Literature review

2.1 Artificial intelligence in online tourism

2.1.1 The digital transformation of tourism

Over the past two decades, the tourism industry has changed significantly with the development of digital technologies (Navío-Marco et al., 2018). The emergence of online booking platforms (such as Booking.com, Expedia and Airbnb) has progressively replaced traditional intermediaries, giving consumers direct access to a vast range of travel products and enabling them to search, compare and book services quickly and independently without having to contact a travel agent (Buhalis, 2019). As a result, competition among platforms has intensified. Platforms no longer compete solely on price or product range but also on the quality of their digital services and the effectiveness of their pricing and recommendation systems (Buhalis & Law, 2008; Navío-Marco et al., 2018).

A key consequence of this transformation is that data has become central to how platforms operate. By collecting information about their users (what they search for, when they book or how much they are willing to pay), platforms can better anticipate demand and refine their pricing strategies. This allows them to better target their offers and optimize their prices, which is why artificial intelligence has become a central tool in the industry (Buhalis & Law, 2008; Buhalis, 2019).

2.1.2 The rise of AI in online tourism

Artificial intelligence (AI) can be broadly understood as the capacity of a system to process and learn from external data in order to accomplish specific objectives through autonomous and flexible decision-making (Kaplan & Haenlein, 2019). Today, AI is now embedded across most stages of the online tourism experience (Buhalis, 2019). Platforms use recommendation systems to suggest destinations and accommodations based on users' past behavior, chatbots to handle customer inquiries and automated tools to monitor and respond to reviews. More broadly, AI enables platforms to process large amounts of data and make decisions such as adjusting prices or ranking search results. These tasks would be impossible to carry out manually at the same speed and scale (Buhalis, 2019).

Among these applications, pricing is one of the most commercially important. It is also the one that consumers encounter most directly. In fact, every time they search for a hotel or a flight, the price displayed has been determined by an automated system, not by a human being. Spann et al. (2025, p. 3) define algorithmic pricing as *"the use of programs to automate the setting of prices"*, distinguishing it from traditional pricing by its reliance on real-time data and automated decision rules rather than manual adjustments by managers. In practice, this means that prices on platforms like Booking.com or Expedia can change multiple times a day in response to demand levels, competitor pricing, booking timing or individual user characteristics (Kopalle et al., 2023). In tourism specifically, this type of pricing makes a lot of sense. A hotel room or a flight seat that remains unsold on a given night or day cannot be recovered: its potential revenue is gone forever. Dynamic pricing allows platforms to adjust prices constantly to maximize the chances of selling every available unit (Spann et al., 2025).

At the same time, however, this system creates an experience that many consumers find difficult to understand. Prices can change between two visits to the same page or differ between two users booking the same room. The logic behind these variations is rarely explained. This lack of visibility between the pricing mechanism and the consumer is the central problem this research sets out to examine. It is precisely this gap that makes transparency, or its absence, a critical factor in how consumers perceive and react to these pricing systems (Vomberg et al., 2025; Kizilcec, 2016).

2.2 Algorithmic dynamic pricing

2.2.1 How algorithmic pricing operates and affects consumers

Consumers interacting with algorithmic pricing systems typically have no visibility into how prices are determined. Factors such as demand levels, booking timing or even the consumer's previous searches may influence the price displayed but none of this is communicated to the user. This is what the literature refers to as a "black box" phenomenon: a system that generates outputs without exposing its internal reasoning to those it affects (Basal et al., 2024; Vomberg et al., 2025). A consumer booking a hotel room on an online platform may observe that the price for a given room has changed significantly between two visits to the same page or that a travelling companion received a different price for an identical booking without any explanation being provided. For consumers, this opacity can be frustrating. Without any explanation, price changes may appear random or even unfair, particularly when two people booking the same room end up paying different amounts (Vomberg et al., 2025).

This opacity generates a specific form of consumer uncertainty that goes beyond ordinary price variation (Vomberg et al., 2025). Vomberg et al. (2025) demonstrate that algorithmic dynamic pricing significantly reduces consumer trust in retailers partly because consumers perceive the pricing process as driven by self-serving logic rather than legitimate market conditions. Consumers generally expect prices to be relatively stable and consistent over time. When this expectation is disrupted without explanation, it creates a misalignment between what consumers expect from a pricing relationship and what algorithmic systems actually deliver (Kopalle et al., 2023).

2.2.2 Personalization and price discrimination concerns

A further dimension of the opacity problem concerns price personalization. Algorithmic pricing does not only vary over time but can also vary across consumers. By collecting data on individual behavior (such as past purchases, browsing patterns or geographic location), platforms can display different prices to different users for the exact same product (Priester et al., 2020). For platforms, this practice is simply a way to maximize revenue by charging each consumer according to their willingness to pay (Spann et al., 2025). For consumers, however, it raises serious concerns about fairness, particularly when they suspect they are being charged more than others for the same product (Xia et al., 2004; Kahneman et al., 1986).

When consumers suspect that the price they are shown is based on personal data (such as their browsing history, perceived urgency or loyalty status), feelings of arbitrary and unfair treatment tend to intensify. Xia et al. (2004) demonstrate that consumers evaluate interpersonal price differences as significantly less fair than time-based or demand-driven variations, as the former implies that the platform is exploiting individual characteristics rather than responding to legitimate market conditions. In the tourism context, where transactions involve considerable financial commitment and emotional investment, such perceptions can have direct behavioral consequences including reduced consumer trust, booking abandonment or negative word-of-mouth (Xia et al., 2004; Vomberg et al., 2025).

2.2.3 The role of transparency in algorithmic pricing

The opacity of AI-driven pricing thus emerges as the central problem that this research seeks to address. When consumers cannot understand how a price was determined, they lack the informational basis to evaluate whether it was fair (Kizilcec, 2016). Without this understanding, suspicion and distrust tend to take over (Vomberg et al., 2025). Transparency therefore becomes more than a regulatory obligation. It is a critical factor in how consumers make sense of algorithmic pricing and decide whether to trust a platform enough to complete a booking (De Lucas López et al., 2026).

Dynamic pricing in online tourism is thus not only a revenue management tool: it is a consumer-facing phenomenon with significant psychological implications (Vomberg et al., 2025). As prices are increasingly set by algorithms based on user data, consumers find themselves interacting with systems they cannot observe, understand or question (Spann et al., 2025). The level of information platforms provide about their pricing mechanisms directly affects how consumers perceive fairness perception, consumer trust, and ultimately, their willingness to book (De Lucas López et al., 2026). The following sections develop the theoretical framework for understanding these consequences.

2.3 AI Transparency

2.3.1 Definition of AI transparency

In the context of AI-driven systems, AI transparency can be defined as the extent to which the functioning, inputs and decision-making logic of an algorithm are accessible and understandable to its users (Haresamudram et al., 2023). Rather than being simply present or absent, AI transparency comes in degrees depending on how much information a platform chooses to share about its system's reasoning (Haresamudram et al., 2023; Kizilcec, 2016).

In the context of dynamic pricing, AI transparency refers more specifically to the degree to which a platform communicates why and how prices are algorithmically determined (De Lucas López et al., 2026). This includes disclosing the variables the system considers (e.g., demand levels, booking timing or user history), the logic through which these variables influence price outputs and the extent to which consumers can access this information at the moment of purchase (Haresamudram et al., 2023; De Lucas López et al., 2026). In the absence of such information, consumers cannot evaluate whether the price they are shown is justified, making transparency not just a technical feature, but a key condition for consumer trust (Kizilcec, 2016; Vomberg et al., 2025).

2.3.2 Levels of AI transparency

Transparency in AI systems is not a monolithic concept. It can take different forms depending on the context and the level of information provided (Haresamudram et al., 2023). Haresamudram et al. (2023) propose a three-level framework distinguishing between *algorithmic transparency* (the ability to inspect and understand the internal logic of the model), *interaction transparency* (the clarity of information communicated to the user during their interaction with the system) and *social transparency* (broader organizational openness about how AI is governed and deployed). Although these three levels are distinct, they are closely linked. From a consumer perspective, interaction transparency is the most important. In fact, it refers to the quality and clarity of the explanations provided at the moment of booking (Haresamudram et al., 2023).

This consumer-facing dimension of transparency aligns closely with what Kizilcec (2016) identifies as the key mechanism through which algorithmic systems shape user attitudes. In an experimental study of an algorithmic grading interface, Kizilcec demonstrates that providing explanations for system outputs restores consumer trust among users whose expectations were violated. Excessive information was found to erode consumer trust rather than build it, suggesting that effective transparency is not about maximizing information volume but about delivering the right level of explanation (Kizilcec, 2016). This "Goldilocks" principle, which is the idea that transparency must be neither too little nor too much but just right, has direct implications for the design of AI-driven pricing disclosures in online tourism platforms (Kizilcec, 2016). In practice, this means that platforms do not need to explain the technical workings of their algorithm, but they should clearly communicate the main factors behind the price displayed to the consumer (Kizilcec, 2016; Haresamudram et al., 2023). In other words, consumers do need to understand what is driving the price they see.

2.3.3 Explainability and informational justification

A closely related concept is explainability, which refers to the capacity of an AI system to communicate the reasoning behind its outputs in a manner that is comprehensible to non-expert users (Haresamudram et al., 2023). While algorithmic transparency addresses whether the system's logic can be inspected, explainability addresses whether it is communicated effectively (Haresamudram et al., 2023). In the context of dynamic pricing, explainability translates into the ability of a platform to provide consumers with clear and meaningful explanations of the factors driving the prices they encounter (Haresamudram et al., 2023).

Vomberg et al. (2025) demonstrate that algorithmic dynamic pricing significantly reduces consumer trust in retailers. This is partly because consumers perceive the pricing process as opaque and self-serving, meaning that it lacks transparency and appears to serve the platform's interests rather than respond to genuine market conditions. While Vomberg et al. (2025) suggest that communication strategies may influence consumer reactions to algorithmic pricing, the specific mechanisms through which transparency shapes fairness perception and consumer trust in online tourism contexts remain underexplored. Similarly, De Lucas López et al. (2026) highlight that transparency in AI-enabled pricing is not simply a technical requirement but an ethical imperative: when platforms provide meaningful justifications for algorithmic decisions, consumers are better positioned to evaluate the fairness of those decisions rather than defaulting to suspicion. In other words, explaining the reasoning behind a price does not only serve regulatory purposes but it directly affects how consumers judge whether that price is fair.

Both studies point to the same underlying mechanism: informational justification (the act of explaining what drives an AI pricing decision) is the primary way through which AI transparency affects how consumers perceive and evaluate prices (Vomberg et al., 2025; De Lucas López et al., 2026). In its absence, consumers lack the information needed to judge whether a price is justified or arbitrary (Kizilcec, 2016). The link between AI transparency and consumer fairness evaluations can be theoretically grounded in procedural justice theory (Thibaut & Walker, 1975), which posits that individuals evaluate the fairness of a decision not only on its outcome but also on the process through which it was reached. When a pricing process is made transparent, consumers can assess whether the procedure was consistent, unbiased and justifiable.

2.3.4 AI Transparency in online tourism

The tourism sector presents a particularly relevant context for examining AI transparency in pricing. Online booking platforms such as Booking.com or Expedia rely heavily on algorithmic systems to set and adjust prices across a wide range of products (such as hotel rooms, flights or rental cars) in real time (Spann et al., 2025). For consumers, travel purchases are often significant, both financially and emotionally (Abrate et al., 2022) and price fluctuations can be dramatic and rapid (Abrate et al., 2022). In this context, the opacity of AI pricing systems has real consequences for consumers: it shapes how they perceive prices (Xia et al., 2004), how much they trust the platform (Vomberg et al., 2025) and ultimately whether they decide to book or not (Abrate et al., 2022).

However, few studies have directly investigated how the level of AI transparency affects the way consumers evaluate the fairness of dynamic pricing in online tourism platforms. The available literature has largely concentrated on retail e-commerce (Vomberg et al., 2025; Spann et al., 2025) and on the ethical and regulatory dimensions of AI pricing (De Lucas López et al., 2026; Basal et al., 2024) with little attention paid to how consumers in online tourism specifically respond to different levels of transparency. This gap motivates the first hypothesis of the present study.

Drawing on procedural justice theory (Thibaut & Walker, 1975) and the empirical findings discussed above (Kizilcec, 2016; Vomberg et al., 2025; De Lucas López et al., 2026), the following hypothesis is proposed:
H1: AI transparency positively influences consumers' fairness perception of dynamic pricing in online tourism platforms.

2.4 Fairness Perception

2.4.1 Definition of fairness perception

Fairness perception, as used in this study, is rooted in the broader concept of price fairness. Price fairness is defined as "*the assessment and associated emotions of whether the difference (or lack of difference) between a seller's price and the price of a comparable other party is reasonable, acceptable or justifiable*" (Xia et al., 2004, p. 3). More broadly, it encompasses a judgment of whether both the price outcome and the process through which it was determined are reasonable and just (Bolton et al., 2003). Unlike an objective measure, price fairness is a subjective judgment. Consumers evaluate the price they encounter by comparing it to a reference point such as what they paid before (past experience), what others are paying (social comparisons) or what they consider a normal market price (prevailing market norms) (Xia et al., 2004; Kahneman et al., 1986). When a price deviates significantly from this reference without apparent justification, consumers tend to perceive it as unfair (Kahneman et al., 1986) regardless of whether the price is objectively high or low (Xia et al., 2004).

2.4.2 Distributive and procedural fairness

Price fairness encompasses two complementary dimensions. Distributive fairness refers to the perceived equity of the price outcome. Namely, whether the price charged seems reasonable compared to what others pay. Procedural fairness, on the other hand, concerns the perceived fairness of the process through which the price was determined regardless of the final amount (Xia et al., 2004). Building on the procedural justice framework developed by Thibaut and Walker (1975), Leventhal (1980) proposed several procedural rules that individuals use to evaluate whether a decision-making process is fair. These include consistency, referring to the extent to which procedures are applied uniformly across individuals and over time, as well as accuracy which concerns whether decisions rely on valid and reliable information. In addition, Shapiro et al. (1994) demonstrated that explanations are perceived as more adequate when they are specific, reasonable and practically useful. Applied to algorithmic pricing, this suggests that AI transparency disclosures are more likely to enhance fairness perception when they provide concrete and understandable information about how prices are determined rather than vague or generic statements. These insights inform both the conceptual logic underlying H1 and the design of the experimental manipulation presented in Chapter 3.

2.4.3 The role of reference prices and social comparison

The principle of dual entitlement (Kahneman et al., 1986) provides a theoretical framework for understanding how consumers form fairness judgments in pricing contexts. It proposes that consumers believe they are entitled to a reference price while acknowledging that companies are entitled to a reference profit. When an observed price violates this implicit social contract without justification (for example, when a platform raises prices simply because demand is high), consumers tend to perceive it as unfair (Kahneman et al., 1986).

In algorithmic pricing environments, this comparison dynamic is further complicated by the fact that prices may differ across consumers based on factors they are rarely aware of, such as personal data, browsing behavior or booking timing (Spann et al., 2025). Priester et al. (2020) demonstrate that personalized dynamic pricing generates stronger unfairness perceptions than uniform dynamic pricing, as consumers suspect that price differences reflect personal data exploitation rather than legitimate market conditions. When consumers discover that a fellow traveller paid significantly less for the same hotel room through the same platform, the resulting sense of inequity is a clear violation of the dual entitlement principle (Xia et al., 2004). The role of social comparison in fairness evaluations is amplified in online environments, where price transparency tools such as price comparison websites make it increasingly easy for consumers to discover price differences (Vomberg et al., 2025). As algorithmic pricing becomes more widespread and consumers grow more aware of its practices, fairness perceptions are likely to play an increasingly important role in shaping their booking decisions (Abrate et al., 2022).

2.4.4 Fairness perception in online tourism platforms

In the context of dynamic pricing, the evaluation of fairness becomes particularly sensitive (Abrate et al., 2022). Prices fluctuate rapidly and often without visible explanation, making it difficult for consumers to apply stable reference points. Abrate et al. (2022), in an empirical study using Booking.com data, demonstrate that price variability directly reduces consumers' perceived fairness, especially when price changes are large and unexplained. This finding highlights a fundamental tension in algorithmic pricing: what allows platforms to optimize revenue also makes it harder for consumers to understand and evaluate the prices they are shown (Abrate et al., 2022; Vomberg et al., 2025).

Tourism services (such as hotel rooms, flights or travel packages) are intangible, heterogeneous and often purchased well in advance under conditions of uncertainty (Parasuraman et al., 1985). Given the high financial stakes and irreversibility of tourism purchases, consumers are especially sensitive to pricing practices they perceive as unfair or arbitrary (Xia et al., 2004). Consumers in the tourism sector have long been exposed to price variability through yield management practices, which they have progressively come to accept as a legitimate feature of the industry (Kimes, 2002). The rise of AI-driven dynamic pricing has pushed these limits further, introducing levels of price personalization and variability that go beyond traditional yield management (Abrate et al., 2022; Vomberg et al., 2025). While consumers in the tourism context generally tolerate moderate price variation, they react negatively when price changes are rapid, large or perceived as based on personal data rather than market conditions (Abrate et al., 2022). When consumers lack access to the reasoning behind a price (why it changed, based on what data and compared to whom), they have no basis to assess whether it is legitimate. In such conditions, opacity itself becomes a driver of perceived unfairness (Kizilcec, 2016; Vomberg et al., 2025).

The distinction between distributive and procedural fairness is central in this context: a consumer may find a price acceptable if the process behind it is clearly explained, even if the amount itself is higher than expected. This is precisely why transparency (which acts on the procedural dimension) plays such a central role in shaping fairness perception (Priester et al., 2020). In the present study, the experimental manipulation varies the level of AI transparency while keeping the price constant across conditions. The fairness perception measured therefore reflects the procedural dimension rather than the distributive dimension.

In sum, fairness perception in dynamic pricing is shaped by both the price outcome itself and the perceived legitimacy of the process through which it was determined (Xia et al., 2004). In the present study, fairness perception refers specifically to the procedural dimension of price fairness, capturing whether consumers judge the algorithmic pricing process as transparent, consistent and justifiable, independently of whether they consider the resulting price to be high or low (Xia et al., 2004; Colquitt, 2001). Since AI transparency directly influences the consumer's ability to evaluate procedural legitimacy, it is expected to have a significant and positive effect on fairness perception (Kizilcec, 2016). Fairness perception, once formed, is expected to translate into more positive relational beliefs toward the platform, most notably consumer trust. This relationship is consistent with the broader justice literature, which identifies procedural fairness as a key antecedent of trust (Lind & Tyler, 1988).

This leads to the formulation of the second hypothesis:
H2: Fairness perception of AI dynamic pricing positively influences consumer trust.

2.5 Consumer Trust

2.5.1 Definition of consumer trust

Trust is a foundational concept in consumer behavior research, defined broadly as a consumer's willingness to be vulnerable to the actions of another party based on the expectation that the latter will act in a benevolent, honest and competent manner (Mayer et al., 1995). In online environments, this definition takes on particular significance: unlike in a physical store where a consumer can interact directly with staff or inspect a product, online transactions require consumers to rely entirely on the platform's interface, reputation and communicated information (McKnight et al., 2002). Consumer trust thus acts as a substitute for information: when consumers cannot verify a platform's pricing logic or intentions, their willingness to trust compensates for this uncertainty and makes the transaction possible (McKnight et al., 2002).

In traditional e-commerce literature, trust is primarily directed toward the platform or vendor as the entity responsible for delivering the service and handling the transaction (McKnight et al., 2002). In the specific context of AI-driven pricing, however, trust extends beyond a purely relational belief toward a firm to also encompass confidence in the automated system through which the platform operates: its reliability, fairness and competence as a decision-making agent (Shin, 2021; Kizilcec, 2016).

The present study therefore conceptualizes consumer trust as a consumer's confidence that the platform, acting through its algorithmic pricing system, will behave honestly, competently and in a manner that serves their interests rather than exploiting them. The object of trust remains the platform but this trust is specifically formed through perceptions of the AI system the platform uses to set prices. In this sense, perceptions of the AI pricing system function as a critical antecedent of trust formation, shaping how consumers evaluate the platform's intentions and behavior in algorithmic environments. Research on human–AI trust shows that individuals form trust judgments toward algorithmic systems based on their perceived reliability, transparency and fairness (Glikson & Woolley, 2020). Similarly, explainability and transparency have been identified as key drivers of trust in AI systems (Shin, 2021). In pricing contexts, opacity in algorithmic decision-making has been shown to undermine trust in the platform by triggering suspicion about its motives (Vomberg et al., 2025).

According to McKnight et al. (2002), online trust comprises two interrelated dimensions: trusting beliefs, which capture whether consumers view the platform as honest and competent and trusting intentions, which reflect their readiness to engage with and depend on it. Both are influenced by how transparent and fair the platform's practices are perceived to be (McKnight et al., 2002). In the context of AI-driven pricing, trusting beliefs are particularly sensitive: when consumers perceive that prices are set by an opaque algorithm without clear justification, their confidence in the platform's honesty and competence is likely to erode (Vomberg et al., 2025).

2.5.2 Consumer trust in e-commerce and online tourism platforms

In the online tourism sector, consumer trust takes on additional significance because bookings are not only made in advance but are often financially irreversible (Nguyen & Nguyen, 2025). Cancellation fees, non-refundable rates and deposit requirements mean that a misplaced consumer trust can translate directly into financial loss. This heightens the perceived risk of the transaction and amplifies the importance of consumer trust as a decision-making resource (Nguyen & Nguyen, 2025).

Consumers booking through platforms such as Booking.com or Expedia must trust not only that the service will be delivered as described but also that the pricing mechanism they encountered was fair, consistent and free from manipulative intent (Vomberg et al., 2025).

Vomberg et al. (2025) demonstrate that algorithmic dynamic pricing systematically erodes consumer trust in the platform, particularly because the opacity of the pricing process triggers suspicion about the platform's motives. This trust deficit has direct behavioral consequences: consumers who distrust a platform's pricing are more likely to engage in extended price search, delay their purchase or switch to a competitor. Conversely, platforms that communicate pricing logic clearly are better positioned to retain consumer trust and consequently, to convert browsing behavior into actual bookings (Vomberg et al., 2025).

2.5.3 Fairness perception as an antecedent of consumer trust

The relationship between fairness perception and consumer trust is one of the most consistently supported findings in the marketing and organizational justice literature. According to Lind and Tyler (1988), perceiving a process as fair leads people to trust the authority or institution behind it. Further research has confirmed this relationship in commercial contexts, including e-commerce platforms where pricing decisions are increasingly automated (Abrate et al., 2022; Priester et al., 2020).

Consumers who perceive a pricing process as transparent and justifiable are more inclined to trust the platform behind it, as they feel it is acting honestly rather than arbitrarily (Lind & Tyler, 1988).

This link is particularly relevant in algorithmic pricing contexts, where consumers simultaneously evaluate both the platform and the technological system through which pricing decisions are made. Abrate et al. (2022) find that consumers who perceive dynamic pricing on Booking.com as procedurally fair report significantly higher trust in the platform than those who perceive the pricing as arbitrary or discriminatory. Similarly, Priester et al. (2020) show that providing clear justifications for personalized price differences considerably improves both fairness perception and consumer trust, even when the price itself remains higher than a uniform alternative. These findings reinforce the conceptual logic of the present model: fairness perception, shaped by AI transparency, functions as a direct antecedent of consumer trust.

2.5.4 Trust as a risk-reduction mechanism in AI pricing contexts

Trust not only results from fairness evaluations but also plays an active role in helping consumers deal with uncertainty, giving them enough confidence to complete a transaction despite not fully understanding the pricing process (McKnight et al., 2002). In environments characterized by information asymmetry, such as AI-driven pricing platforms where algorithms operate in ways that consumers cannot fully observe or understand, trust allows consumers to proceed with a transaction without requiring complete transparency about the system's logic (McKnight et al., 2002). This risk-reduction function of consumer trust is especially critical in tourism contexts, where the combination of high financial commitment and limited reversibility of bookings makes consumers particularly dependent on their confidence in the platform (Nguyen & Nguyen, 2025).

Kizilcec (2016) highlights a dual function of trust in algorithmic systems. On one hand, transparency builds consumer trust by reducing perceived opacity. On the other hand, consumer trust enables them to accept that they cannot fully understand the system while still feeling confident enough to proceed. This suggests that in the tourism context, AI transparency and consumer trust are closely intertwined: transparency shapes trust by reducing perceived arbitrariness, while consumer trust enables them to act decisively despite remaining uncertainty about the pricing algorithm's full complexity (Kizilcec, 2016).

Taken together, the literature establishes consumer trust as playing a critical mediating role between fairness perception and purchase behavior. Consumers who trust the platform, based on its AI pricing practices and perceived fairness, are consequently more likely to complete a booking.

This relationship leads to the formulation of the third hypothesis:
H3: Consumer trust positively influences purchase intention.

2.6 Purchase Intention

2.6.1 Definition of purchase intention

Purchase intention captures a consumer's self-reported readiness to complete a transaction in a given context. Rather than measuring actual behavior, it reflects the psychological state that precedes the purchase decision, making it a widely used and validated proxy for behavioral outcomes in consumer research (Pavlou, 2003; Dodds et al., 1991). In online environments, purchase intention captures the consumer's readiness to convert from browsing to buying. This transition depends heavily on the psychological states formed during the evaluation process, including perceived value, risk, fairness and consumer trust (Fauzi et al., 2021).

In the context of AI-driven dynamic pricing on online tourism platforms, purchase intention represents the ultimate behavioral outcome of the consumer's engagement with the pricing system (Nguyen & Nguyen, 2025). A consumer who has been exposed to a pricing mechanism, whether transparent or opaque, will form evaluations of that mechanism's fairness, develop relational beliefs toward the platform and ultimately decide whether to proceed with a booking (Kizilcec, 2016). Purchase intention is thus the point at which psychological processes translate into commercially relevant behavior (Pavlou, 2003).

2.6.2 Consumer trust as a driver of purchase intention

Consumer trust has consistently ranked among the most influential predictors of purchase intention in e-commerce research with empirical studies confirming that trust levels significantly explain consumers' willingness to complete online transactions (McKnight et al., 2002; Rainy & Dhanekula, 2025). Online transactions inherently expose consumers to vulnerability (Mayer et al., 1995). They must transfer financial resources to a platform before the service is delivered with no guarantee of delivery beyond their confidence in the platform's integrity (McKnight et al., 2002). Consumer trust reduces the perceived risk inherent in this vulnerability and thus lowers the psychological barrier that prevents consumers from committing to a purchase (Lăzăroiu et al., 2020).

In tourism-specific contexts, this relationship is amplified. Nguyen and Nguyen (2025) demonstrate that consumers of AI-driven pricing in the tourism sector are significantly more likely to complete a booking when they trust the platform's pricing practices, even when the price itself is not the lowest available. This finding suggests that consumer trust goes beyond risk reduction: consumers who trust a platform are willing to accept a higher price in exchange for the assurance that their transaction will be handled fairly and reliably (Nguyen & Nguyen, 2025). By contrast, platforms that fail to generate consumer trust (whether through opaque pricing, perceived discrimination or unexplained price volatility) are likely to face higher abandonment rates and reduced conversion (Vomberg et al., 2025).

2.6.3 The indirect effect of AI Transparency on Purchase Intention

While consumer trust directly drives purchase intention, the present model proposes that AI transparency influences purchase intention not through a direct path, but through its prior effects on fairness perception and consumer trust. This logic is consistent with prior findings on the mediating role of psychological states in algorithmic contexts (Kizilcec, 2016; Vomberg et al., 2025). This indirect pathway reflects the sequential cognitive process consumers follow when exposed to an AI pricing system: they first assess the information available about how prices are determined, form a judgment about its fairness, develop or withdraw trust accordingly and ultimately decide whether to proceed with a booking (Kizilcec, 2016).

This mechanism is supported by the broader mediation literature in marketing, which consistently shows that the effects of process-level variables (such as transparency or explanation quality) on behavioral outcomes are largely carried by intervening psychological states rather than operating directly (Vomberg et al., 2025; Abrate et al., 2022). In other words, AI transparency does not directly determine whether a consumer completes a booking, but rather shapes the psychological conditions that make such a decision possible, by increasing fairness perception and thereby building the consumer trust needed to act (Vomberg et al., 2025).

Abreu da Silva (2024) demonstrates that pricing transparency has no direct effect on purchase intention once fairness perception and consumer trust are accounted for, confirming the mediating logic of the present model. That said, this evidence stems from a general e-commerce environment. The present study extends this logic to online tourism platforms, where service intangibility, financial irreversibility and algorithmic opacity create a particularly demanding context for consumer decision-making (Abrate et al., 2022; Nguyen & Nguyen, 2025). This pattern is consistent with the present model's prediction that fairness and trust carry the explanatory weight of the transparency-behavior relationship.

In this setting, AI transparency, fairness perception and consumer trust form an interdependent chain of psychological conditions that collectively determine whether a consumer converts from consideration to commitment. Each variable is a necessary step: without AI transparency, fairness perception cannot be evaluated; without fairness perception, consumer trust cannot be formed; and without consumer trust, purchase intention remains out of reach (Kizilcec, 2016; Lind & Tyler, 1988; McKnight et al., 2002).

These considerations lead to the formulation of the fourth hypothesis, describing the indirect effect of AI transparency on purchase intention:
H4: The positive effect of AI transparency on purchase intention is mediated by fairness perception and consumer trust such that AI transparency influences fairness perception, which in turn influences consumer trust, which ultimately influences purchase intention.

2.7 AI Literacy

2.7.1 Definition of AI literacy

As AI systems become increasingly embedded in everyday consumer experiences, individuals differ substantially in their capacity to understand and critically engage with these systems. Long and Magerko (2020) define this capacity as a set of competencies enabling individuals to evaluate what AI is, how it works and what implications it carries. Carolus et al. (2023) extend this conceptualization by identifying distinct measurable facets, including the ability to use, understand, detect and ethically assess AI systems. It encompasses both cognitive dimensions, such as knowledge of how algorithms operate and how data is used to generate outputs and evaluative dimensions, such as the ability to critically assess the reliability, fairness and limitations of AI-based systems (Long & Magerko, 2020; Carolus et al., 2023).

It should be noted that AI literacy is distinct from general digital literacy, which refers more broadly to the ability to use digital tools and use online environments (Carolus et al., 2023). More specifically, AI literacy refers to the ability to understand how algorithmic systems operate and to critically evaluate whether the decisions they produce are legitimate, fair and trustworthy (Long & Magerko, 2020). Haresamudram et al. (2023) establish that users' capacity to comprehend the technology they interact with is a prerequisite for transparency to produce its intended effects. When this capacity is absent, even well-designed disclosures may fail to generate meaningful understanding. In the context of AI-driven pricing, this suggests that AI transparency explanations can only enhance fairness perception if consumers possess sufficient AI literacy to interpret them.

2.7.2 AI Literacy as a boundary condition for transparency effects

The effect of AI transparency on fairness perception is not uniform across consumers (Carolus et al., 2023). Individual differences in the ability to process and interpret algorithmic information are expected to shape how strongly transparency disclosures influence fairness evaluations. A consumer who receives an explanation stating that prices are adjusted based on demand, booking timing or seasonal factors will only benefit from this disclosure if they possess the cognitive tools to understand what it means and assess its legitimacy (Kizilcec, 2016).

For consumers with high AI literacy, transparency disclosures provide genuinely actionable information (Kizilcec, 2016). They can contextualize the explanation within their understanding of how algorithmic systems function, assess whether the disclosed factors are legitimate and consistent and form a reasoned judgment about the fairness of the pricing process. The disclosure effectively reduces informational uncertainty and perceived arbitrariness, translating into a more favorable evaluation of the pricing process. In other words, when a consumer understands how an algorithm works, being told how a price was determined feels informative and reassuring rather than abstract or suspicious. For these consumers, the positive effect of transparency on fairness perception is therefore expected to be strong (Shin, 2021).

For consumers with low AI literacy, however, the same disclosure may have a more limited or even negligible effect. Without the conceptual framework to interpret what it means for a price to be "*adjusted by an AI system based on demand*", the explanation may feel abstract, opaque or even alienating (Shin, 2021). Research on information processing suggests that when individuals lack the cognitive resources to elaborate on incoming information, they tend to rely on heuristic cues rather than systematic evaluation. That means that a complex algorithmic explanation may not serve as a credible or interpretable fairness cue for low-literacy consumers (Chaiken, 1980). In short, AI transparency without comprehension cannot generate fairness perception.

Shin (2021) further reinforces this argument by showing that the positive effect of algorithmic explanations on fairness perception is conditional on users' ability to understand the reasoning behind them. This capacity, referred to as "*causability*", determines whether transparency disclosures translate into meaningful fairness evaluations or remain cognitively inaccessible, regardless of their quality or detail. Applied to the dynamic pricing context, these findings suggest that the positive effect of AI transparency on fairness perception is conditional on consumers' level of AI literacy (Kizilcec, 2016). Simply put, an explanation of how a price was determined will only feel fair to consumers who understand what that explanation means.

2.7.3 AI Literacy in the consumer pricing context

Dynamic pricing algorithms in online tourism platforms are highly complex. They process multiple variables simultaneously, including real-time demand, booking timing, seasonal factors and competitive prices (Vomberg et al., 2025). Most consumers have little to no knowledge of how these mechanisms work (Haresamudram et al., 2023), which makes AI literacy a particularly relevant moderator in this context.

As established above, transparency disclosures do not affect all consumers equally. Their effectiveness depends on whether consumers have the AI literacy needed to process and interpret the information provided. De Lucas López et al. (2026) reinforce this point by arguing that effective transparency in AI-enabled pricing requires not only disclosure but also accessibility. This means that explanations must be adapted to the consumer's level of understanding. A technically detailed algorithmic explanation may be highly informative for an AI-literate consumer while remaining completely opaque for one who lacks this interpretive capacity.

The present study therefore expects AI literacy to moderate the relationship between AI transparency and fairness perception: high-literacy consumers will respond more strongly to transparency disclosures, translating them into more favorable fairness evaluations, while low-literacy consumers will show a weaker response (Shin, 2021; Kizilcec, 2016). This moderation effect represents one of the study's primary theoretical contributions, as it addresses a gap in the literature. Most studies on AI transparency treat consumers as having identical levels of understanding, without accounting for the significant variation in their capacity to process algorithmic information (Long & Magerko, 2020; Carolus et al., 2023).

This reasoning leads to the formulation of the fifth hypothesis:

H5: AI literacy moderates the relationship between AI transparency and fairness perception, such that the positive effect of AI transparency on fairness perception is stronger for consumers with higher AI literacy than for those with lower AI literacy.

2.8 Conceptual model

The theoretical relationships can be integrated into a unified conceptual (Figure 1) model that captures the proposed chain of effects linking AI transparency to consumer purchase intention in online tourism platforms.

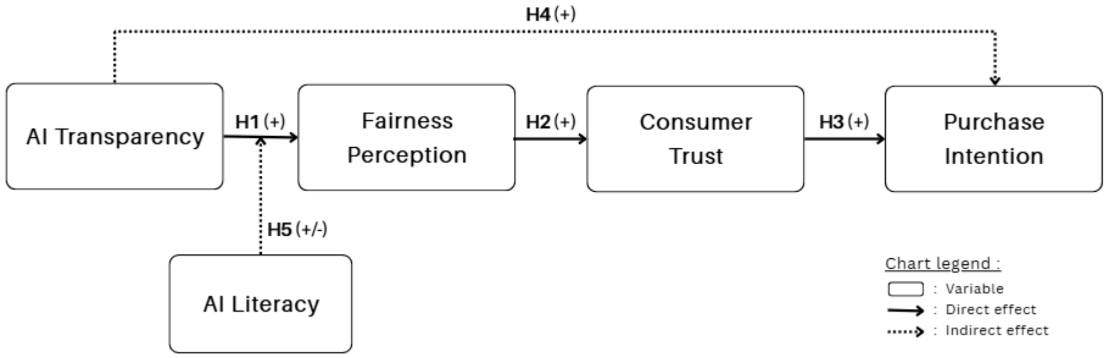


Figure 1. *Conceptual research model*

The model positions AI transparency as the independent variable, operationalized as the degree to which a platform discloses and explains the factors driving its algorithmic pricing decisions. Fairness perception and trust function as successive mediating variables: AI transparency shapes consumers' evaluation of the pricing process (fairness perception), which in turn influences their relational beliefs toward the platform (consumer trust), ultimately translating into a behavioral intention (purchase intention). AI literacy is included as a moderating variable, conditioning the strength of the relationship between AI transparency and fairness perception.

As discussed in the literature review, below are the proposed hypotheses for this study:

Table 1. *Summary of proposed hypotheses*

H1	AI transparency positively influences fairness perception of dynamic pricing in online tourism platforms.
H2	Fairness perception positively influences consumer trust in online tourism platforms.
H3	Consumer trust positively influences purchase intention.
H4	The positive effect of AI transparency on purchase intention is mediated by fairness perception and consumer trust such that AI transparency influences fairness perception, which in turn influences consumer trust, which ultimately influences purchase intention.
H5	AI literacy moderates the relationship between AI transparency and fairness perception, such that the positive effect of AI transparency on fairness perception is stronger for consumers with higher AI literacy than for those with lower AI literacy.

2.9 Synthesis and research hypotheses

The preceding sections have developed a sequential theoretical framework linking AI transparency to consumer purchase intention in online tourism platforms. Building on established research in price fairness, consumer trust and information processing, the model proposes a coherent cognitive pathway from informational disclosure to behavioral intention.

This framework makes three distinct contributions to existing literature. First, it integrates constructs that are typically studied in isolation into a single sequential model applied to algorithmic dynamic pricing in online tourism. Second, the sequential mediation logic provides a theoretically justified account of how and why transparency influences behavior, identifying the psychological mechanisms through which it operates. Third, the moderating role of AI literacy introduces a boundary condition that accounts for individual differences in the capacity to process algorithmic information, an aspect that most existing studies on AI transparency overlook.

Together, these elements position the present study as both a theoretical extension of existing frameworks and an empirical response to a context where systematic evidence is still limited. The following chapter details the methodological approach used to empirically test these hypotheses.

3 Research design

This chapter outlines the research design developed to conduct the present study. First, the chosen methodology will be described and justified. This will be followed by a discussion of the sampling strategy and data collection process. Subsequently, the research instrument will be presented. Finally, the measurement methods used to operationalize the key constructs of the study will be discussed.

3.1 Methodology

This study, which investigates how AI transparency in algorithmic dynamic pricing influences consumer purchase intention in online tourism platforms, adopts a quantitative and conclusive research design. According to Malhotra et al. (2017), a conclusive research design aims to "*describe specific phenomena, to test specific hypotheses and to examine specific relationships*", which directly aligns with the objectives of the present research. In fact, the five hypotheses (H1–H5) were derived from the existing literature and are empirically tested in the present study. More specifically, this research employs a causal research design, defined as one "*used to obtain evidence of cause-and-effect (causal) relationships*" (Malhotra et al., 2017). This approach is particularly appropriate given that the research seeks to examine the causal effect of AI Transparency on behavioral outcomes (such as fairness perception, consumer trust or purchase intention) while also examining sequential mediation and the moderating role of AI literacy.

To operationalize this causal logic, the present study employs a one-factor experimental design in which a single factor is manipulated across conditions. That factor is the level of AI transparency, communicated to participants through a simulated online flight booking platform. This factor is tested across two levels: low transparency (Condition A) and high transparency (Condition B). A between-subjects design is adopted, exposing each participant to one condition only. Participants receive either Condition A or Condition B but never both. They are thus randomly assigned to one of the two conditions. This ensures that any pre-existing differences between them, such as general attitudes toward AI or prior familiarity with dynamic pricing platforms, are distributed equally across both groups. As a result, any difference observed between conditions can be causally attributed to the transparency manipulation itself rather than to participant characteristics (Shadish, Cook & Campbell, 2002). A between-subjects design was preferred as isolating each participant to a single condition preserves the authenticity of their responses.

The experimental manipulation relies on scenario-based vignettes (see Appendix A, Figures A1-A4) . This method presents participants with a realistic situation incorporating fictitious elements and asks them to respond as if they were actually in it. In the present study, this takes the form of a simulated flight booking page from FlyNow, which is a fictitious online airline platform. This approach allows for precise control over the stimuli presented to participants, while maintaining sufficient realism to generate meaningful responses (Rungtusanatham, Wallin & Eckerd, 2011). Its relevance is further supported by its successful application in research on fairness perceptions in pricing contexts (Xia, Monroe & Cox, 2004), algorithmic transparency (Kizilcec, 2016) and AI-driven dynamic pricing (Priester, Robbert & Roth, 2020). All dependent and mediating constructs are operationalized using validated Likert-scale items drawn from established literature, as detailed in Section 3.4.

3.2 Sample

The target population consists of adults aged 18 and over, regardless of nationality, who are proficient in French or English and have previously used an online platform to book a flight. Participants are not expected to have any prior knowledge of artificial intelligence, as the study focuses on how average consumers perceive and react to AI-driven pricing.

This research relied on a convenience sample, whereby participants were selected based on their accessibility and willingness to participate (Malhotra et al., 2017). Data were collected over a one-week period in early May 2026, from Monday evening to Sunday morning, through four main channels. First, personal networks were mobilized through word-of-mouth, reaching friends, family members and acquaintances meeting the inclusion criteria. Second, the survey was shared online across social media platforms. On Facebook, it was posted across more than ten groups dedicated to travel, selected for their relevance to individuals with an interest in flight booking and trip planning. On LinkedIn, it was published via a personal profile, reaching a broad audience of professional and academic contacts (see Appendix B, Figures B1–B2 for the recruitment poster and social media caption). Third, the survey was posted on SurveyCircle, an online research community platform in which participants complete other members' surveys in exchange for points that increase the visibility of their own study. Fourth, printed flyers featuring a QR code linking to the survey were distributed in public spaces including bars, supermarket entrances and workplaces. Flyers were often handed directly to potential participants in these locations, accompanied by a brief verbal explanation of the study's academic context and objectives. Across all communication channels (see Appendix B, Figures B1–B2), participants were explicitly informed that their responses would remain fully anonymous. Although the questionnaire was made available in both French and English, the vast majority of responses were collected in French, reflecting the linguistic profile of the primary distribution channels used.

For each experimental condition, a minimum of 60 valid responses was required to ensure adequate statistical power, resulting in an overall target of approximately 120 valid responses across both groups. This target was determined through a dual justification. First, it is consistent with the sample sizes reported in comparable experimental studies on algorithmic pricing and fairness perceptions. In fact, Priester et al. (2020) relied on approximately 64 participants per condition in their between-subjects experiment on personalized dynamic pricing and Kizilcec (2016) conducted his transparency experiment with approximately 34 participants per condition. The present study's target of 60 valid responses per condition is therefore broadly aligned with the sample sizes reported in these reference studies. Second, in line with the statistical power recommendations formulated by Cohen (1992) for experimental designs, a sample of 64 participants per group is required to achieve a statistical power of 0.80 at a significance level of $\alpha = 0.05$ when detecting a medium effect size ($d = 0.50$). With a minimum of 60 valid responses per condition, the present study closely meets this standard, ensuring sufficient sensitivity to detect theoretically meaningful effects. A total of 244 responses were collected, of which 167 were fully completed. After applying the predefined exclusion criteria (attention check, comprehension check, and filter question), 36 responses were removed, yielding a final valid sample of 131 respondents (70 in Condition A and 61 in Condition B). Both conditions therefore exceed the minimum threshold of 60 valid responses per group.

To ensure data quality, one eligibility criterion was applied before participation: participants were asked whether they had previously booked a flight online and those who answered "No" were automatically redirected to a disqualification page. After data collection, three quality criteria were applied to the completed responses. First, participants who selected the incorrect answer on the attention check item were excluded, as this suggests they did not read the questionnaire carefully. Second, participants who scored 3 or below on the comprehension check item (CC) were excluded, as a low score indicates insufficient understanding of the experimental scenario. Third, all participants were verified to be aged 18 or older, as required for ethical compliance. Including responses that did not meet these criteria would risk compromising the internal validity of the data collected.

3.3 Experimental design and research instrument

Data were collected through a self-administered online questionnaire hosted on LimeSurvey, the survey platform institutionally provided by HEC Liège. This platform was considered particularly appropriate for this research given its support for automatic randomization of participants across conditions, real-time data collection monitoring and the guarantee of respondent anonymity. The questionnaire was available in both French and English, selectable from the introduction page, to broaden accessibility and ensure linguistic comprehension. To preserve the integrity of participants' responses, backward navigation was disabled throughout the questionnaire, preventing participants from returning to and modifying their previous answers.

Before proceeding to the experimental scenario, participants were asked a screening question to verify their eligibility, namely whether they had previously used an online platform to book a flight. Participants who did not meet this criterion were redirected to a disqualification page and excluded from further participation. Those who qualified were then automatically and randomly assigned to one of two experimental conditions, low transparency (Condition A) or high transparency (Condition B), ensuring an approximately equal distribution across groups. To avoid any potential influence of the experimental context on AI literacy scores, the AI literacy scale was administered prior to exposure to the experimental stimulus, alongside the screening question and a general question about participants' prior experience with online flight booking platforms. Following random assignments, participants proceeded to their assigned experimental stimulus, after which they completed a transition statement, manipulation check items, the main measurement scales assessing AI transparency, fairness perception, consumer trust and purchase intention, an attention check item and four demographic questions.

To guarantee that participants approached the survey with appropriate engagement, the study was presented to them under the neutral title "Étude sur la perception des prix sur les plateformes de voyage" or "Study on price perception on travel platforms", so that participants remained unaware of the study's focus on AI and pricing transparency before encountering the experimental stimulus. The full questionnaire is available in Appendix C (Figures C1–C9).

For this research, FlyNow, a fictitious online airline booking platform, was created exclusively for the purposes of this study. FlyNow does not exist and has no affiliation with any real airline or travel company. The decision to use a fictitious rather than an existing platform was motivated by the need to control for any brand-related biases that could influence participants' evaluations. This choice follows Geuens and De Pelsmacker's (2017) recommendation to use fictitious brands in experiments, as they prevent existing brand attitudes from interfering with participants' reactions to the manipulation. For instance, a participant with a negative prior experience with a real airline might respond differently from one who has never used that platform. By creating FlyNow as a neutral and unfamiliar brand, all participants were placed in an equivalent position, ensuring that their responses reflected only their reactions to the experimental manipulation.

Participants were presented with a booking summary page from FlyNow, representing the final step before payment confirmation. This page depicts a one-way economy class flight from Brussels (BRU) to Barcelona (BCN) on Tuesday, June 14, 2026 (flight FN 402, Boeing 737-800, 2h05, non-stop, departing at 07:15 and arriving at 09:20). The selected fare is the Essential option, totaling 119.99€

(99.00€ base fare + 20.99€ taxes and fees). The flight details and pricing were deliberately chosen to reflect a plausible and typical short-haul European booking scenario. A price of 119.99€ for a Brussels–Barcelona flight was considered sufficiently realistic to engage participants without being extreme enough to trigger strong price-related reactions independent of the experimental manipulation. All elements of this page are held strictly constant across both experimental conditions. The only element that differs between conditions is the pricing information box, which operationalizes the two levels of AI transparency tested in this experiment. Before being exposed to the booking page, all participants were presented with a standardized instruction, displayed identically across both conditions, asking them to project themselves into a real booking situation and respond accordingly.

In Condition A (low AI transparency), the pricing information box displays a vague notice with no reference to artificial intelligence: *"The displayed fare may vary. It is valid only at the time of your consultation."* In Condition B (high AI transparency), participants are presented with a detailed explanation of the pricing mechanism. The text explicitly names the AI system responsible for the price calculation and introduces a structured table displaying four factors driving the algorithm (demand, seasonality, time before departure and booking history) alongside their real-time status and directional influence on the displayed price. Rather than simply enumerating input variables, this format makes the pricing logic explicit at the level of each individual factor. By disclosing the current value of each factor (e.g., "High demand", "Peak season") and its directional effect on the price (↑), it enables participants to understand not only what drives the price but why the current price is set at this level. A closing statement reassures participants that the same algorithm applies equally to all passengers. The experimental stimuli for both conditions and both languages are presented in Appendix A (Figures A1–A4).

The design of the AI transparency manipulation was informed by the procedural justice criteria discussed in Section 2.4. Specifically, showing the four pricing factors and their current values (e.g., "High demand" and "Peak season") addresses Leventhal's (1980) accuracy rule. The closing statement that the same algorithm applies equally to all passengers reflects the consistency rule. Rather than simply listing the factors driving the price, the manipulation displays each factor's real-time status and its directional effect on the price (↑). This approach follows Kizilcec's (2016) distinction between disclosing that a system uses certain inputs and actually showing how those inputs influence the output. This level of specificity also responds to Shapiro et al.'s (1994) finding that explanations are perceived as more adequate when they are concrete and practically useful. For instance, stating that "High demand increases the price" is more informative than simply mentioning that demand is one of the factors considered.

As all measurement items refer to FlyNow's AI system, a brief transition statement was displayed after the stimulus to inform participants that FlyNow uses an artificial intelligence (AI) system to determine its fares in real time, which ensure consistent item interpretation across both conditions. The following section details the scales used to measure each variable.

3.4 Measures

All variables were measured using validated Likert-scale items drawn from established literature and adapted to the present study's experimental context. Each item was reformulated to explicitly reference FlyNow's AI system and the flight booking scenario, guaranteeing consistency and relevance across all measurement scales. All items were introduced by the phrase "I find that..." to standardize the response format and align with the natural language used in the experimental scenario. Each item was rated on a 7-point Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree). All items were made available in both French and English, which is in line with the bilingual design of the questionnaire.

To prevent any potential influence of the experimental stimulus on AI literacy scores, the AI literacy scale was administered before participants were exposed to the experimental conditions. It was included together with the eligibility screening question and a general measure of prior experience with online flight booking platforms. This placement reflects the moderating role of AI literacy in the conceptual model. As a stable individual characteristic, it was measured independently of the experimental context to avoid any contamination of responses by the transparency manipulation.

Each variable in the conceptual model was operationalized using validated scales from the existing literature, adapted to the FlyNow experimental context as described below. AI transparency was measured using 3 items adapted from Kizilcec's (2016) conceptualization of algorithmic transparency. While AI transparency is operationalized through experimental manipulation in this study, it is also measured as a perceived construct to verify the effectiveness of the stimulus. As Kizilcec (2016) does not propose a standardized multi-item scale but rather operationalizes transparency through the amount and type of information displayed in the interface itself, the items for this variable were specifically adapted to capture participants' perceived access to information and their understanding of the pricing logic. This approach ensures that the measurement remains faithful to the conceptual dimensions of transparency, namely disclosure and clarity, identified in the original study while being tailored to the FlyNow context. Fairness perception was measured using 5 items adapted from Colquitt (2001) and Xia, Monroe and Cox (2004), combining procedural justice and price fairness perspectives to capture the dual nature of consumers' fairness evaluations in a dynamic pricing context. The scale includes one item capturing an overall fairness judgment (FP1: "I find that the price proposed by FlyNow is fair") while the other four items (FP2–FP5) specifically target procedural fairness criteria such as rule clarity, consistency and process legitimacy. This combination reflects Xia et al.'s (2004) integrated conceptualization of price fairness, which encompasses both outcome and process evaluations within a single construct. Consumer trust was operationalized using 5 items adapted from Sirdeshmukh, Singh and Sabol (2002), a scale specifically developed to measure consumer trust toward service providers in online environments, making it particularly suitable for the online booking context of FlyNow. Purchase intention was assessed using 4 items adapted from Grewal, Krishnan, Baker and Borin (1998), one of the most widely replicated scales for measuring behavioral intentions in retail and e-commerce settings. AI literacy was measured using 4 items adapted from the MAILS scale developed by Carolus, Koch, Straka, Latoschik and Wienrich (2023), a validated tool measuring individuals' general understanding of AI systems and their ability to evaluate them critically.

To verify the effectiveness of the experimental manipulation, two manipulation check items were included. These items assessed the extent to which participants perceived the pricing information as clear, detailed and transparent, allowing for a comparison of AI transparency levels across conditions. A comprehension check item was also included to assess whether participants had adequately understood the experimental scenario. Participants who scored 3 or below on this item were excluded from the analyzes, as a low score indicates insufficient engagement with the stimulus. Finally, an attention check item was embedded in the middle of the questionnaire, asking participants to select a specific day of the week regardless of their personal preference. Participants who failed this item were also excluded. Table 2 provides a complete overview of all measurement items used in the study, presented in the order in which they appeared in the questionnaire.

Table 2. *Summary of measurement scales*

Variable	Author(s)	Code	Item (English)	Item (French)
AI Literacy *(Moderator)*	Carolus, Koch, Straka, Latoschik & Wienrich (2023) MAILS	AIL1	I understand how artificial intelligence works in general.	Je comprends de manière générale comment fonctionne l'intelligence artificielle.
		AIL2	I understand how an AI system makes decisions.	Je comprends comment un système d'IA prend des décisions.
		AIL3	I am able to use AI-based tools in my daily life.	Je suis capable d'utiliser des outils basés sur l'IA dans ma vie quotidienne.
		AIL4	I am able to recognize when an AI system is used in an online service.	Je suis capable de reconnaître lorsqu'un système d'IA est utilisé dans un service en ligne.
Comprehension check		CC1	I find that I understood the information presented in this scenario well.	Je trouve que j'ai bien compris les informations présentées dans ce scénario.
Manipulation check		MC1	I find that the explanations about how FlyNow's AI system works were detailed.	Je trouve que les explications sur le fonctionnement du système d'IA de FlyNow étaient détaillées.
		MC2	I find that the functioning of FlyNow's AI system was clearly explained to me.	Je trouve que le fonctionnement du système d'IA de FlyNow m'a été clairement expliqué.
AI Transparency *(Independent Variable)*	Kizilcec (2016)	AIT1	I find that I have access to sufficient information about how FlyNow's AI system calculates prices.	Je trouve que j'ai accès à suffisamment d'informations sur la manière dont le système d'IA de FlyNow calcule les prix.
		AIT2	I find that I can understand the logic used by FlyNow's AI system to set this price.	Je trouve que je peux comprendre la logique utilisée par le système d'IA de FlyNow pour fixer ce prix.
		AIT3	I find that the amount of information about how FlyNow's AI system works is sufficient.	Je trouve que la quantité d'informations sur le fonctionnement du système d'IA de FlyNow est suffisante.
Fairness Perception *(Mediator 1)*	Colquitt (2001) ; Xia, Monroe & Cox (2004)	FP1	I find that the price proposed by FlyNow is fair.	Je trouve que le prix proposé par FlyNow est équitable.
		FP2	I find that FlyNow follows clear rules to set its prices.	Je trouve que FlyNow suit des règles claires pour fixer ses prix.

		FP3	I find that FlyNow applies the same rules to all customers.	Je trouve que FlyNow applique les mêmes règles à tous les clients.
		FP4	I find that FlyNow's pricing process is fair.	Je trouve que le processus de tarification de FlyNow est juste.
		FP5	I find that the price was determined appropriately.	Je trouve que le prix a été déterminé de manière correcte.
Consumer Trust *(Mediator 2)*	Sirdeshmukh, Singh & Sabol (2002)	CT1	I trust the FlyNow platform.	Je fais confiance à la plateforme FlyNow.
		CT2	I find that FlyNow acts in the best interest of customers.	Je trouve que FlyNow agit dans l'intérêt des clients.
		CT3	I find that FlyNow is a reliable platform.	Je trouve que FlyNow est une plateforme fiable.
		CT4	I find that FlyNow is competent in setting prices.	Je trouve que FlyNow est compétente pour fixer les prix.
		CT5	I find that FlyNow operates honestly.	Je trouve que FlyNow fonctionne de manière honnête.
Attention Check		AC	Forced-choice item: select Monday regardless of personal preference.	Item à choix forcé: sélectionner Lundi indépendamment de la préférence personnelle.
Purchase Intention *(Dependent Variable)*	Grewal, Krishnan, Baker & Borin (1998)	PI1	I would consider booking this flight at the displayed price.	Je serais susceptible de réserver ce vol au prix affiché.
		PI2	It is likely that I would proceed with the booking in this situation.	Il est probable que je procède à la réservation dans cette situation.
		PI3	I would seriously consider completing this reservation.	J'envisagerais sérieusement de finaliser cette réservation.
		PI4	I would be willing to confirm this purchase at the indicated price.	Je serais prêt(e) à confirmer cet achat au tarif indiqué.
Demographics		D1	Age	Âge
		D2	Gender	Genre
		D3	Highest level of education	Niveau d'études le plus élevé
		D4	Frequency of online flight booking per year	Fréquence d'utilisation des plateformes de réservation en ligne par an

4 Results

This chapter presents the empirical findings of the study. It begins with a description of the data cleaning process and the final sample, followed by reliability analyzes, descriptive statistics and the manipulation check. The core of the chapter tests the five research hypotheses through independent samples t-tests, linear regressions and a sequential mediation analysis with bootstrapping.

4.1 Data cleaning and sample description

4.1.1 Data cleaning

As outlined in the methodology, a total of 244 responses were recorded through the online survey platform LimeSurvey. Of these, 167 were fully completed. From the completed responses, 36 participants were excluded based on three predefined quality criteria. First, 24 respondents failed the attention check item, which required selecting a specific answer (Monday) to demonstrate attentive reading. Second, six respondents scored 3 or below on the comprehension check item (CC1), indicating insufficient understanding of the experimental scenario. Third, five respondents both answered “No” to the filter question and failed the attention check. One additional respondent was excluded for failing both the comprehension and attention checks simultaneously. All participants in the final sample were aged 18 or older, meeting the minimum age requirement for participation. These criteria resulted in a final valid sample of 131 respondents.

4.1.2 Sample description

The final sample comprised 131 valid respondents, randomly assigned to one of two experimental conditions: 70 participants were assigned to Condition A (low AI transparency) and 61 to Condition B (high AI transparency). The sample was predominantly female (62.6%) and relatively young, with a mean age of 33.1 years (SD = 16.1). In terms of educational background, 43.5% held a Master’s degree and 42.7% a Bachelor’s degree, which reflects the largely academic profile of the sample. Regarding online booking behavior, the majority of participants (70.2%) reported booking flights online one to two times per year. Seven participants reported "never" booking flights on an annual basis. However, these participants had confirmed past online booking experience through the screening question and were therefore retained in the sample, as the frequency question captured annual regularity rather than lifetime experience (see Table 3 or Appendix D, Tables D1–D5 for detailed frequency distributions and sample description).

Table 3. *Sample demographics*

Variable	Category	Total (N=131)	Cond. A (n=70)	Cond. B (n=61)	%
Gender	Female	82	46	36	62.6
	Male	48	24	24	36.6
	Prefer not to say	1	0	1	0.8
Age	M (SD)	33.1 (16.1)	30.4 (13.3)	36.3 (18.5)	
	18–24	77	45	32	58.8
	25–34	17	9	8	13.0
	35–44	3	2	1	2.3
	45–54	12	8	4	9.2
	55+	22	6	16	16.8
Education	Bachelor's degree	56	26	30	42.7
	Master's degree	57	35	22	43.5
	Secondary education	16	7	9	12.2
	Doctorate	1	1	0	0.8
	Other	1	1	0	0.8
Booking frequency	1 to 2 times	92	45	47	70.2
	3 to 5 times	18	13	5	13.7
	More than 5 times	14	10	4	10.7
	Never	7	2	5	5.3

Note. Cond. A = Low AI Transparency condition; Cond. B = High AI Transparency condition. N = 131.

4.1.3 Group comparability

To ensure that the random assignment produced equivalent groups, the two experimental conditions were compared on key demographic variables. Independent samples t-tests were used for the continuous variable (age), while chi-square tests of independence were conducted for categorical variables (gender, education level and booking frequency).

As shown in Table 4, no significant differences were found between the two conditions on gender ($\chi^2 = 1.61$, $p = .447$), education ($\chi^2 = 4.91$, $p = .297$) or booking frequency ($\chi^2 = 6.87$, $p = .076$). The comparison on age yielded a significant result ($t = -2.15$, $p = .033$) with participants in Condition B ($M = 36.3$, $SD = 18.5$) being slightly older than those in Condition A ($M = 30.4$, $SD = 13.3$). However, since age is not a central variable in the conceptual model and the difference remains modest, this was not considered a threat to internal validity. Overall, the two groups were sufficiently comparable in terms of demographic characteristics to proceed with the experimental analyzes (see Appendix D, Tables D5–D8 for full statistical outputs).

Table 4. *Group comparability tests*

Variable	Cond. A	Cond. B	Test statistic	df	p
Age (M, SD)	30.4 (13.3)	36.3 (18.5)	$t = -2.150$	129.0	.033
Gender			$\chi^2 = 1.609$	2	.447
Education			$\chi^2 = 4.905$	4	.297
Booking frequency			$\chi^2 = 6.870$	3	.076

Note. No significant differences between conditions on any demographic variable (all p > .05), except age (p = .033), which is borderline.

4.2 Reliability analysis

Before testing the research hypotheses, the internal consistency of each measurement scale was assessed. Internal consistency ensures that the items composing each scale coherently measure the same construct, which is a necessary condition for meaningful statistical analysis (Hair et al., 2019). Cronbach's alpha was used as the primary reliability indicator, as it remains the most widely adopted measure of scale reliability in social science research (Tavakol & Dennick, 2011). A threshold of .70 is generally considered acceptable for establishing adequate reliability (Nunnally, 1978; Tavakol & Dennick, 2011). The results are summarized in Table 5.

The scales for Consumer trust (α = .900), fairness perception (α = .897), purchase intention (α = .966) and AI transparency (α = .876): all demonstrated good to excellent internal consistency. All are well above the conventional threshold of .70 (Nunnally, 1978). Item-rest correlations for these scales ranged from .522 to .95 which confirm that individual items contributed meaningfully to their respective constructs.

The AI literacy scale presented a slightly lower Cronbach's alpha of .679, marginally below the conventional .70 threshold. Item-level analysis indicated that AIL4 exhibited the weakest item-rest correlation (.339), and its removal would raise the alpha to .703. However, all four items were retained in the main analyzes for two reasons. First, the scale was drawn from the validated MAILS instrument (Carolus et al., 2023) and modifying its structure without strong justification would compromise its theoretical integrity. Second, the shortfall from the threshold was minimal and unlikely to meaningfully affect the reliability of the measure. To ensure that this choice did not affect the conclusions drawn from the analysis, H5 was additionally tested with the reduced three-item scale. The results were substantively identical, lending empirical support to the retention of the original four-item measure (full item-level reliability statistics are reported in Appendix D, Tables D9–D14).

Table 5. *Reliability analysis*

Scale	Items	Cronbach's α	95% CI	Item-rest r range
AI Literacy	4	.679	[.562, .795]	.175 – .677
Manipulation Check	2	.728	[.616, .840]	.578
AI Transparency	3	.876	[.830, .921]	.589 – .824
Fairness Perception	5	.897	[.866, .927]	.385 – .836
Consumer Trust	5	.900	[.863, .937]	.654 – .810
Purchase Intention	4	.966	[.953, .980]	.833 – .932

Note. Conventional threshold: α ≥ .70. AI Literacy is slightly below (.679); removing AIL4 improves to .703.

4.3 Descriptive statistics and correlations

Table 6 presents the means, standard deviations and Pearson correlations among the five main variables, all measured on 7-point Likert scales. Descriptive statistics provide an overview of the central tendencies and variability of responses across the sample, while bivariate correlations offer a preliminary assessment of the direction and strength of the relationships between constructs before proceeding to hypothesis testing.

Several noteworthy patterns emerged from the correlation matrix. The strongest correlation was observed between fairness perception and consumer trust ($r = .714$, $p < .001$). This finding is consistent with the theoretical expectation that fairness evaluations serve as a precursor to trust formation. Consumer Trust and Purchase Intention were also strongly correlated ($r = .603$, $p < .001$), supporting the well-established link between trust and behavioral intentions in e-commerce research. AI Transparency showed a moderate positive correlation with Fairness Perception ($r = .586$, $p < .001$), providing preliminary support for H1.

It is also worth noting that AI Transparency was not significantly correlated with Purchase Intention ($r = .037$, $p = .675$), suggesting that the effect of transparency on purchase intention is not direct but rather operates through the mediating variables. This pattern will be formally examined in the mediation analysis (H4).

AI Literacy did not show significant correlations with any of the main variables (all $p > .05$). While this does not preclude a moderating effect, it provides an early indication that its role in shaping the relationship between AI Transparency and Fairness Perception may be limited in this sample (see Appendix D, Table D15 for the complete correlation matrix).

Table 6. *Descriptive statistics and correlations*

Variable	M	SD	1	2	3	4	5
1. AI Literacy	4.98	0.88	—				
2. AI Transparency	3.81	1.38	.091	—			
3. Fairness Perception	4.10	1.09	.058	.586***	—		
4. Consumer Trust	3.90	1.01	–.007	.356***	.714***	—	
5. Purchase Intention	4.38	1.39	.091	.037	.344***	.603***	—

Note. N = 131. * $p < .05$, ** $p < .01$, *** $p < .001$.

4.4 Manipulation check

Before testing the hypotheses, it was essential to verify that the experimental manipulation of AI transparency was successful. Specifically, this involved assessing whether participants in Condition B (high transparency) perceived significantly more transparency than those in Condition A (low transparency).

Two sets of measures were used to assess the manipulation. The first consisted of the manipulation check items (MC1 and MC2, $\alpha = .728$) which directly evaluated whether participants found the AI pricing explanations to be detailed and clear. The second was the AI transparency scale (AIT1–AIT3, $\alpha = .876$) which captured broader perceptions of algorithmic transparency.

Independent samples t-tests were conducted using Welch's correction, which adjusts the degrees of freedom to account for potential differences in variance between groups and does not assume equal variances across conditions (Delacre et al., 2017). The results revealed significant differences between conditions in both measures. On the manipulation check items, participants in Condition B scored significantly higher ($M = 4.87$, $SD = 1.13$) than those in Condition A ($M = 3.74$, $SD = 1.35$), $t(128.8) = 5.24$, $p < .001$, Cohen's $d = 0.91$. On the AI transparency scale, the difference was even more pronounced: Condition B ($M = 4.65$, $SD = 1.07$) versus Condition A ($M = 3.07$, $SD = 1.19$), $t(128.9) =$

7.99, p < .001, Cohen's d = 1.39. Both effect sizes qualify as large according to Cohen's (1988) conventions (d > 0.80).

These results confirm that the experimental manipulation was effective: participants exposed to the high transparency condition perceived the AI pricing system as significantly more transparent than those in the low transparency condition (see Table 7). Detailed group descriptives are available in Appendix D in Tables D16–D17.

Table 7. *Manipulation check and H1*

Variable	Cond. A M (SD)	Cond. B M (SD)	t	df	p	Cohen's d
MC_mean	3.74 (1.35)	4.87 (1.13)	−5.243	128.8	< .001	0.907
AIT_mean	3.07 (1.19)	4.65 (1.07)	−7.990	128.9	< .001	1.389
FP_mean (H1)	3.85 (1.06)	4.38 (1.05)	−2.909	126.8	.004	0.509

Note. Cond. A = Low Transparency (n = 70); Cond. B = High Transparency (n = 61). Welch's t-test reported. All tests are two-tailed.

4.5 Hypothesis testing

4.5.1 H1: AI Transparency and Fairness Perception

The first hypothesis posited that higher AI transparency would lead to greater perceived fairness of the pricing system. To test this, an independent samples t-test (Welch's correction) was conducted comparing Fairness Perception scores between the two experimental conditions.

The results supported H1. Participants in the high transparency condition (M = 4.38, SD = 1.05) perceived the pricing as significantly fairer than those in the low transparency condition (M = 3.85, SD = 1.06), t(126.8) = 2.91, p = .004, Cohen's d = 0.51. The effect size is considered medium according to Cohen's (1988) conventions, indicating a meaningful practical difference. These findings suggest that when consumers are provided with clear explanations about how an AI-driven pricing system operates, they are more likely to evaluate the pricing process as fair.

4.5.2 H2: Fairness Perception and Consumer Trust

The second hypothesis predicted that higher perceived fairness would positively influence consumer trust. A simple linear regression was conducted with fairness perception as the predictor and consumer trust as the dependent variable.

The model was significant, $F(1, 129) = 134.26$, $p < .001$ and explained 51.0% of the variance in consumer trust ($R^2 = .510$), as presented in Table 8. Fairness perception was a strong positive predictor of consumer trust ($\beta = .665$, $t = 11.59$, $p < .001$, 95% CI [0.552, 0.779]). H2 is therefore strongly supported. This result aligns with the theoretical expectation, grounded in procedural justice theory, that when individuals perceive a decision-making process as fair, they are more likely to develop trust toward the entity responsible for that process (see Appendix D, Tables D18–D19).

4.5.3 H3: Consumer Trust and Purchase Intention

The third hypothesis stated that higher consumer trust would lead to greater purchase intention. A simple linear regression was conducted with consumer trust as the predictor and Purchase Intention as the dependent variable.

The model was significant, $F(1, 129) = 73.62$, $p < .001$, explaining 36.3% of the variance in Purchase Intention ($R^2 = .363$). Consumer trust was a strong positive predictor ($\beta = .826$, $t = 8.58$, $p < .001$, 95% CI [0.635, 1.016]). H3 is therefore supported. This result is consistent with the well-established relationship between trust and behavioral intentions in online environments and suggests that this mechanism also operates in the context of AI-driven dynamic pricing in tourism. The regression results for both hypotheses are reported in Table 8 (see Appendix D, Tables D18–D19).

Table 8. *Linear regression (H2 and H3)*

	Predictor	Outcome	β	SE	t	p	R²
H2	FP_mean	CT_mean	0.665	0.057	11.59	< .001	.510
H3	CT_mean	PI_mean	0.826	0.096	8.58	< .001	.363

Note. β = unstandardized regression coefficient.

4.5.4 H4: Sequential Mediation

The fourth hypothesis proposed that the effect of AI transparency on purchase intention is sequentially mediated by fairness perception and consumer trust. Specifically, the hypothesized mechanism follows the path: AI transparency → fairness perception → consumer trust → purchase intention. The results of the mediation analysis are illustrated in Figure 2 and detailed in Table 9 (see Appendix D, Table D20 for the full SEM output).

This hypothesis was tested using structural equation modeling (SEM) in JASP with maximum likelihood estimation and bootstrap resampling (1,000 iterations) to construct bias-corrected confidence intervals for the indirect effects.

The path coefficients were as follows. The path from AI transparency to fairness perception (a_1) was significant ($\beta = 0.248$, $p = .002$) confirming that the experimental condition influenced fairness evaluations. The path from fairness perception to consumer trust (a_2) was also significant ($\beta = 0.721$, $p < .001$) indicating that fairness strongly predicts trust when controlling for the experimental condition. The path from consumer trust to purchase intention (b) was significant ($\beta = 0.723$, $p < .001$). The direct effect of AI transparency on purchase intention ($c' = -0.107$) was not significant ($p = .127$).

The standardized sequential indirect effect ($a_1 \times a_2 \times b$) was 0.129 (SE = 0.048, $p = .006$), with a 95% bootstrap confidence interval of [0.036, 0.223]. Since the confidence interval does not include zero, the sequential mediation is statistically significant. H4 is therefore supported.

The total effect of AI transparency on purchase intention was not significant ($c = 0.022$, $p = .795$), while the indirect effect through the sequential pathway was significant. This pattern corresponds to what Zhao, Lynch, and Chen (2010) classify as an "indirect-only mediation" in which the effect of the independent variable on the outcome operates entirely through the mediating chain. In other words, transparency does not directly influence purchase intention, but it enhances fairness perceptions, which in turn build consumer trust, which ultimately increases the willingness to purchase.

The model accounted for 6.2% of the variance in fairness perception (R^2 = .062), 51.1% in consumer trust (R^2 = .511), and 38.9% in Purchase Intention (R^2 = .389).

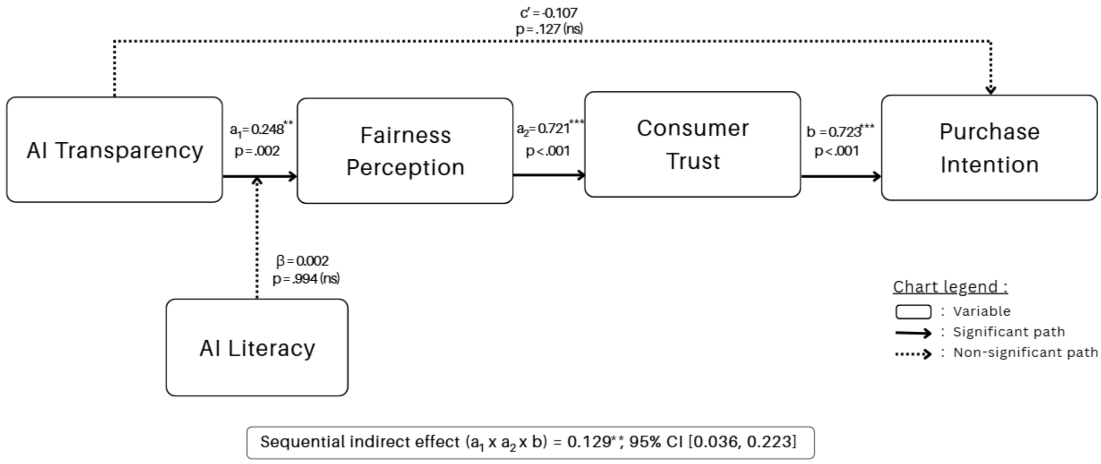


Figure 2. *Sequential mediation model with path coefficients*

Note. Solid lines indicate significant paths; dashed lines indicate non-significant paths.

Table 9. *Sequential mediation (H4)*

Path	Estimate (Std.)	SE	p	95% CI Lower	95% CI Upper
a1: Transparency → Fairness	0.248	0.081	.002	0.090	0.406
a2: Fairness → Trust	0.721	0.045	< .001	0.633	0.810
b: Trust → Purchase Int.	0.723	0.085	< .001	0.557	0.890
c' (direct): Transp. → PI	−0.107	0.070	.127	−0.244	0.030
f: Fairness → PI	−0.147	0.099	.140	−0.341	0.048
Indirect (sequential)	0.129	0.048	.006	0.036	0.223
Direct effect	−0.107	0.070	.127	−0.244	0.030
Total effect	0.022	0.086	.795	−0.147	0.192

Note. Standardized estimates from structural equation modeling (ML estimation) with bootstrap confidence intervals (1,000 samples). N = 131.

4.5.5 H5: Moderation by AI Literacy

The fifth hypothesis predicted that AI literacy would moderate the relationship between AI transparency and fairness perception, such that individuals' level of AI literacy would influence the strength of the effect of transparency on fairness evaluations.

To test this hypothesis, a hierarchical linear regression was conducted with fairness perception as the dependent variable. In Model 0, AI transparency (condition) and AI literacy (mean-centered) were entered as predictors. In Model 1, the interaction term (Condition × AI literacy) was added.

Model 0 was significant, $F(2, 128) = 5.01$, $p = .008$, $R^2 = .073$. The main effect of the experimental condition was significant ($\beta = 0.580$, $t = 3.09$, $p = .002$), consistent with H1. The main effect of AI literacy was not significant ($\beta = 0.132$, $t = 1.24$, $p = .219$).

The addition of the interaction term in Model 1 did not significantly improve the model ($\Delta R^2 = .000$, $p = .994$). The interaction coefficient was virtually zero ($\beta = 0.002$, $t = 0.007$, $p = .994$). This indicates that AI literacy does not moderate the effect of transparency on fairness perception. H5 is therefore not supported.

A simple slopes analysis further confirmed this result: the effect of AI transparency on fairness perception was nearly identical at low AI literacy (−1 SD: $b = 0.579$) and high AI literacy (+1 SD: $b = 0.582$). Additionally, a sensitivity analysis using the three-item version of the AI literacy scale (excluding AIL4 to improve reliability) produced the same conclusion (interaction $\beta = 0.066$, $p = .743$). The full moderation results are presented in Table 10 (see Appendix D, Table D21).

These results indicate that the effect of transparency on fairness perception is not contingent on individuals' level of AI literacy. Whether consumers are more or less familiar with AI systems, they appear to respond to transparency information in a similar manner.

Table 10. *Moderation analysis (H5)*

Predictor	B	SE	β	t	p	95% CI
(Intercept)	3.172	0.862		3.681	< .001	[1.467, 4.877]
Condition (0 = A, 1 = B)	0.573	1.104	0.264	0.519	.605	[−1.612, 2.757]
AI Literacy (centered)	0.131	0.166	0.106	0.790	.431	[−0.197, 0.460]
Condition × AI Literacy	0.002	0.218	0.003	0.007	.994	[−0.429, 0.432]

Note. Dependent variable: Fairness Perception. AI Literacy is mean-centered. $R^2 = .073$, $F(3, 127) = 3.313$, $p = .022$. The interaction term is not significant.

4.6 Summary of findings

Table 11 provides an overview of all hypothesis testing results.

Table 11. *Summary of hypothesis testing*

Hypothesis	Relationship	Key statistic	p	Result
H1	Transparency → Fairness	d = 0.509	.004	Supported
H2	Fairness → Trust	β = 0.665	< .001	Supported
H3	Trust → Purchase Intention	β = 0.826	< .001	Supported
H4	Sequential mediation	indirect = 0.129	.006	Supported
H5	AI Literacy moderates H1	β = 0.002	.994	*Not supported*

Note. H4 indirect effect is the standardized sequential indirect effect (Transparency → Fairness → Trust → Purchase Intention). H5: the interaction between condition and AI literacy on fairness perception.

Four out of five hypotheses were supported. AI transparency significantly enhanced fairness perception (H1), which in turn strongly predicted consumer trust (H2). Trust was a significant predictor of purchase intention (H3), as expected. The sequential mediation from transparency through fairness and trust to purchase intention was confirmed (H4), indicating that the mechanism operates as a cognitive chain: consumers first evaluate the fairness of the pricing process, then form trust beliefs and ultimately translate those beliefs into behavioral intentions.

The only unsupported hypothesis concerned the moderating role of AI literacy (H5). Contrary to expectations, AI literacy did not significantly influence how consumers processed or responded to transparency information. The implications of these findings are discussed in the following chapter.

5 Discussion

This chapter interprets the findings of the study by connecting them to the broader body of research on consumer responses to algorithmic pricing systems. It begins with a brief summary of the key results, followed by a systematic comparison with the existing literature for each hypothesis. Particular attention is given to the indirect-only mediation pattern (H4) and the unexpected null finding regarding AI literacy (H5). The chapter concludes with a discussion of the study's theoretical contributions, managerial implications, strengths and limitations.

5.1 Key findings

The study tested a sequential model in which AI transparency in algorithmic dynamic pricing influences consumer purchase intention through fairness perception and consumer trust, with AI literacy as a moderator. The results supported four of the five hypotheses. Participants exposed to higher AI transparency perceived the pricing system as fairer (H1, $d = 0.51$) and this fairness perception was a strong predictor of consumer trust (H2, $\beta = .665$, $R^2 = .51$), which in turn drove purchase intention (H3, $\beta = .826$, $R^2 = .36$). The sequential mediation from AI transparency through fairness perception and consumer trust to purchase intention was confirmed (H4, indirect = 0.129, 95% CI [0.036, 0.223]), revealing an indirect-only mediation pattern in which AI transparency does not directly affect purchase intention but operates entirely through the mediating chain. The only unsupported hypothesis was the moderation by AI literacy (H5, $\beta = 0.002$, $p = .994$), which had virtually no effect on the transparency–fairness relationship.

5.2 Interpretation and comparison with existing literature

5.2.1 H1: AI Transparency and Fairness Perception

The finding that AI transparency significantly enhances fairness perception ($d = 0.51$) is consistent with the procedural justice literature, which holds that individuals evaluate the fairness of outcomes partly based on the transparency and quality of the process that produced them (Lind & Tyler, 1988). In the context of AI-driven dynamic pricing, this means that when consumers are given a clear explanation of how prices are determined, they are more likely to view the pricing process as legitimate rather than arbitrary. More specifically, participants who received an explanation of the factors driving the price (such as real-time demand and booking timing) evaluated the pricing process as significantly fairer than those who were given no insight into how the price was set. This result reinforces a central principle of procedural justice theory: consumers' fairness judgments are shaped less by the price they are asked to pay than by whether the process behind that price is made visible and comprehensible.

This result aligns closely with several empirical studies in pricing literature. Priester et al. (2020), in a between-subjects experiment on personalized dynamic pricing, found that providing explanations for pricing differences significantly improved fairness perception. The present study extends their findings by demonstrating that this transparency effect holds not only for personalized pricing but also for general AI-driven dynamic pricing in a tourism-specific context. Kizilcec (2016) found a comparable effect in algorithmic grading, where transparency improved consumer trust specifically among users who received an unexpectedly unfavorable outcome. Extending this logic to the pricing context, the present study, even though the price shown was identical across conditions, the simple presence of an explanation was sufficient to shift fairness perceptions, suggesting that the process itself, and not the outcome, drives this evaluation. This is consistent with the procedural fairness dimension described by Xia et al. (2004).

Furthermore, Vomberg et al. (2025) demonstrated that the opacity of algorithmic dynamic pricing systematically erodes consumer trust and triggers suspicion about the platform's motives. The present study provides complementary evidence from the opposite direction: by making the algorithm transparent, a platform can reduce this suspicion and improve fairness evaluations. The medium effect size ($d = 0.51$) suggests that transparency is a meaningful but not overwhelming factor, consistent with the idea that it is a necessary but not sufficient condition for fairness. Additional factors, such as the perceived reasonableness, are also likely to influence this evaluation (Abrate et al., 2022).

5.2.2 H2: Fairness Perception and Consumer Trust

The strong relationship between fairness perception and consumer trust ($\beta = .665$, $R^2 = .51$) confirms one of the most solid findings in the organizational justice and marketing literatures. When consumers perceive a process as fair, they are more inclined to believe that the entity behind that process is acting with integrity and in good faith (Lind & Tyler, 1988; McKnight et al., 2002). The strength of this association is notable: in the present model, fairness perception explained over half of the variance in consumer trust, underscoring its role as a central antecedent of trust formation in algorithmic pricing contexts.

This finding converges with Abrate et al. (2022), who demonstrated using Booking.com data that consumers who perceive dynamic pricing as procedurally fair report significantly higher trust in the platform than those who perceive the pricing as arbitrary or discriminatory. Priester et al. (2020) added a further nuance by showing that providing justifications for personalized price differences improved both fairness perceptions and consumer trust, even when the price itself remained higher than a uniform alternative. That suggests that the process of explaining matters more than the outcome it produces. Nguyen and Nguyen (2025) confirmed this pattern specifically in the Vietnamese tourism context, demonstrating that fairness perception of AI-driven pricing positively influences consumer trust. The present study extends these findings by demonstrating that the fairness–trust link holds in an experimental setting, where fairness perception was directly shaped by varying the level of information provided about the pricing algorithm.

5.2.3 H3: Consumer Trust and Purchase Intention

The finding that consumer trust strongly predicts purchase intention ($\beta = .826$, $R^2 = .36$) extends the trust–intention relationship (McKnight et al., 2002; Pavlou, 2003) to the specific context of AI-driven dynamic pricing in tourism. Nguyen and Nguyen (2025) found a consistent pattern in the Vietnamese tourism context: consumers who trust an AI pricing platform are significantly more likely to complete a booking, even when the price is not the lowest available, suggesting that trust serves not simply as a risk-reduction mechanism but as a signal that the platform's pricing practices are reliable and acceptable.

Vomberg et al. (2025) reinforced this finding from the opposite perspective: consumers who distrust a platform’s pricing are more likely to engage in extended price search, delay their purchase or switch to a competitor. In high-stakes environments such as tourism bookings, where financial commitment is substantial and transactions are often irreversible, trust becomes the decisive psychological condition for converting browsing into purchasing (Lăzăroiu et al., 2020). The present results confirm that this mechanism operates in AI-driven pricing contexts, where the opacity of the algorithm adds an additional layer of uncertainty that consumer trust must overcome.

5.2.4 H4: Sequential Mediation

The sequential mediation analysis revealed that AI transparency influences purchase intention entirely through the fairness–trust pathway. The direct effect of AI transparency on purchase intention was non-significant ($c' = -0.107$, $p = .127$) as was the total effect ($c = 0.022$, $p = .795$). This pattern corresponds to what Zhao et al. (2010) describes as indirect-only mediation. Although the total effect is close to zero, this does not mean that transparency has no influence on purchase intention. From a theoretical perspective, this finding offers the clearest insight into how AI transparency operates on behavioral outcomes.

This result means that simply telling consumers how prices are determined does not, in itself, make them more willing to buy. Rather, transparency triggers a cognitive chain: it first allows consumers to evaluate whether the pricing process is fair, this fairness perception then shapes their trust toward the platform and consumer trust, ultimately, drives the purchase decision. Each step is necessary: without AI transparency, fairness perception cannot be adequately evaluated; without fairness perception, consumer trust cannot be established; and without consumer trust, purchase intention does not follow.

This pattern is not unique to the present study. In a related experiment comparing normal pricing versus AI pricing, Abreu da Silva (2024) found that the indirect path from the pricing scenario to purchase intention through fairness perception was significant while the direct path was not. Although the two studies differ in their independent variable, as Abreu da Silva (2024) manipulated the type of pricing mechanism whereas the present study manipulated the level of transparency, both converge on the same conclusion: the effect on purchase intention is not direct but fully transmitted through psychological mediators. This convergence across independent samples and different contexts (general e-commerce vs. online tourism) suggests that the indirect-only pattern reflects a psychological process that holds across different research designs.

The present study extends this finding in two important ways. First, it adds consumer trust as a second sequential mediator. While Abreu da Silva (2024) showed that fairness perception mediates the effect on purchase intention, the present results demonstrate that fairness perception alone does not directly drive the purchase decision. Instead, fairness perception first builds consumer trust and it is consumer trust that ultimately leads to purchase intention. The mediation chain is therefore more complete than previously established. Second, this mechanism is tested in the online tourism context, where consumers face challenges: the service cannot be evaluated before purchase, bookings are often financially irreversible and the pricing logic remains opaque (Abrate et al., 2022; Nguyen & Nguyen, 2025). The fact that even in this demanding context, AI transparency influences purchase intention only through fairness perception and consumer trust confirms that these psychological states are not optional steps but necessary conditions in the consumer's decision process (Vomberg et al., 2025; Kizilcec, 2016).

5.2.5 H5: Null Effect of AI Literacy

Contrary to expectations, AI literacy did not moderate the relationship between AI transparency and fairness perception. The interaction effect was virtually zero ($\beta = 0.002$, $p = .994$) and, as reported in the results section, this absence of moderation held across both simple slopes analysis (0.579 vs 0.582) and an alternative specification of the scale. This null result deserves careful consideration. While certain methodological factors may have contributed, including the limited contextual specificity of the AI literacy scale and the relative homogeneity of the sample (discussed further in the limitations section), the most likely explanation relates to the design of the transparency manipulation itself.

The high transparency condition provided a simple and plain-language explanation of how the AI system determined prices. It did not require any technical knowledge of algorithms or machine learning to be understood. As a result, the explanation was likely equally comprehensible to all participants, whether they had high or low AI literacy. This effectively neutralized the moderating role that literacy was expected to play: if everyone understands the explanation, then differences in AI knowledge no longer matter. This reasoning is supported by Shin (2021), who argues that transparency only influences fairness when the explanation is understandable to the receiver, a property he refers to as causability. De Lucas López et al. (2026) make a similar point, arguing that effective transparency is not just about providing information but about making that information accessible to the audience. Haresamudram et al. (2023) support this interpretation, noting that when transparency disclosures are well designed, even users with limited technical understanding can benefit from them.

The hypothesis, as formulated in the literature review, predicted that AI-literate consumers would benefit more from transparency explanations than consumers with lower AI literacy (Shin, 2021; Kizilcec, 2016). However, because the manipulation was deliberately designed to be accessible to all participants, the experimental conditions may not have allowed this moderation to emerge. The null finding therefore says less about the theoretical validity of the hypothesis than about the conditions under which it was tested.

5.3 Theoretical contributions

This study makes several contributions to existing literature. First, it integrates AI transparency, fairness perception, consumer trust and purchase intention into a single sequential framework, providing a comprehensive account of how transparency influences behavior in AI-driven pricing environments. Prior research has examined these constructs in isolation or in pairs, such as pricing transparency and fairness perception (Priester et al., 2020), fairness perception and consumer trust (Abrate et al., 2022) or consumer trust and purchase intention (Nguyen & Nguyen, 2025). The present study demonstrates how they connect in a coherent cognitive chain, following the sequential path proposed in the conceptual model.

Second, the confirmation of an indirect-only mediation pattern advances our understanding of how AI transparency operates. Rather than directly influencing purchase intention, AI transparency affects consumer behavior only through the psychological states it activates, namely fairness perception and consumer trust. This finding goes against the idea, often implicit in the transparency literature, that providing information is enough to change behavior, and suggests that researchers and platform designers should pay closer attention to the intermediate mechanisms through which transparency produces its effects.

Third, the study extends these findings to the online tourism context, where algorithmic opacity, financial irreversibility and service intangibility create a particularly demanding environment for consumer decision-making (Abrate et al., 2022; Nguyen & Nguyen, 2025). The results demonstrate that the fairness–trust–intention mechanism holds in this high-stakes context, suggesting that the model could potentially apply to other domains where AI-driven pricing is prevalent (such as e-commerce or event ticketing).

Finally, although AI literacy did not moderate the effect of AI transparency on fairness perception, this result remains a meaningful contribution. It suggests that when transparency explanations are designed to be accessible, individual differences in AI competency may be less influential than previously assumed (Shin, 2021; De Lucas López et al., 2026). In the present study, the AI transparency manipulation was designed using plain language and a structured list of pricing factors rather than technical algorithmic details, which may explain why AI literacy did not significantly influence the way participants processed the information. This insight reframes AI literacy not as a universal moderator of transparency effects, but as a conditional one that becomes relevant only when the complexity of the explanation exceeds the comprehension capacity of the audience.

5.4 Managerial implications

The findings carry several practical implications for online tourism platforms and their pricing strategies. The most important takeaway is that transparency pays: not by directly increasing conversion but by activating the psychological conditions that make consumers willing to book. Platforms that explain how their AI pricing works can expect consumers to perceive the pricing as fairer, which builds consumer trust and which ultimately increases booking likelihood.

A key distinction is thatthe indirect-only mediation pattern implies that transparency alone is not sufficient. Platforms must ensure that the explanations they provide are not only present but perceived as fair: what matters equally is what platforms choose to explain. An explanation that reveals discriminatory pricing criteria (for instance, the use of personal data such as browsing history or location to set prices) could produce the opposite effect by triggering unfairness perceptions despite being technically transparent (Priester et al., 2020).

The null finding on AI literacy offers a reassuring insight for practitioners: transparency explanations do not need to be segmented by literacy level. A single and clearly worded explanation can be equally effective for all consumers, regardless of their familiarity with AI. This considerably reduces the complexity of implementation and suggests that the priority should be clarity and accessibility rather than technical sophistication, for instance by naming the factors behind the price in everyday language rather than describing the workings of the algorithm.

Finally, given the strong fairness–trust link ($R^2 = .51$), platforms should consider transparency not merely as a regulatory obligation but as a consumer trust-building strategy. In a competitive market where prices across platforms are often comparable, the platform that best communicates how its prices are determined may gain a meaningful consumer trust advantage and ultimately stand out from its competitors.

5.5 Strengths of the study

The study has several methodological strengths that enhance the credibility of its findings, notably its experimental design, the effectiveness of the manipulation, the reliability of the measurement scales and the integration of multiple theoretical perspectives into a single tested framework.

First, the experimental design with random assignment allows for causal inference regarding the effect of AI transparency on fairness perception, which is a significant advantage over the cross-sectional correlational designs used in much of the existing literature on AI pricing (Vomberg et al., 2025; Abrate et al., 2022). Second, the manipulation check confirmed a strong and unambiguous effect (Cohen's d = 0.91 on the manipulation check items and d = 1.39 on the AI transparency scale), ensuring that the observed differences are attributable to the experimental manipulation rather than to random variation or uncontrolled factors. Third, all core measurement scales demonstrated good to excellent internal consistency (α ranging from .876 to .966). The sequential mediation was tested using bootstrap resampling with 1,000 iterations which is a recommended approach for testing indirect effects (Zhao et al., 2010). Fourth, the study integrates constructs from multiple theoretical traditions, providing one of the few empirical tests that combine procedural justice, trust formation and AI transparency within a single framework.

5.6 Limitations and future research

Despite its contributions, the study is subject to several limitations that should be considered when interpreting the results and that open avenues for future research.

First, the sample was recruited through convenience sampling and consisted predominantly of young and highly educated participants with a largely academic profile (86% held a Bachelor's or Master's degree with 33.1 years as a mean age). This limits the generalizability of the findings to broader consumer populations, particularly older consumers or those with lower digital familiarity, who may respond differently to AI transparency disclosures. Future studies should seek more demographically diverse and representative samples to assess whether the findings hold across different consumer segments.

Second, the study relied on a fictitious platform (FlyNow) and a hypothetical booking scenario. While this approach ensures experimental control by eliminating the influence of pre-existing brand attitudes and platform loyalty, it raises questions about ecological validity, which is the extent to which the experimental findings reflect how consumers would behave in a real-world setting (Shadish, Cook & Campbell, 2002). Consumers interacting with a real platform (with real financial consequences and actual booking outcomes) may process transparency information differently. Future research could replicate the design using real booking interfaces or field experiments with actual platforms to assess whether the effects are held in more realistic decision-making contexts.

Third, the AI literacy scale exhibited marginally low reliability (α = .679, slightly below the conventional threshold of .70) and showed no significant correlations with any of the main study variables (all $p > .05$). The MAILS instrument (Carolus et al., 2023), while validated, was designed to capture general AI competencies across a broad range of domains. In the specific context of dynamic pricing, where the relevant knowledge concerns how algorithms determine prices rather than general AI capabilities, the scale may have lacked the contextual sensitivity needed to differentiate meaningfully between respondents. A domain-specific measure focused on consumers' understanding of algorithmic pricing mechanisms does not yet exist in the literature. Developing such an instrument would be a valuable contribution for future research. Furthermore, participants scored similarly on AI literacy with limited variation across the sample. When a moderator variable does not vary sufficiently across participants, interaction effects become statistically difficult to detect regardless of whether the theoretical mechanism exists (Cohen, 1988). Future research could address this by comparing transparency manipulations with varying levels of technical complexity (for instance a simple plain-language explanation versus a detailed algorithmic account) in order to create conditions where AI literacy differences are more likely to emerge.

Fourth, the study focused on a single tourism product (flight booking) and a single manipulation format (text-based explanation). The generalizability of the findings to other tourism services (hotel bookings, car rentals, package deals) or to other explanation formats (visual dashboards, interactive tools or real-time notifications) remains to be established. Moreover, the study compared only two levels of transparency (low vs. high). This binary design was chosen to maximize the contrast between conditions and ensure a clear manipulation effect but it does not capture the full range of transparency levels that platforms might implement in practice. Future research could explore whether intermediate levels of transparency produce similar effects, as long as the differences between conditions remain perceptible to participants.

Finally, while the sequential mediation model explains a substantial proportion of variance in consumer trust ($R^2 = .51$) and purchase intention ($R^2 = .39$), the variance explained in fairness perception by the transparency manipulation alone was modest ($R^2 = .06$). This means that transparency is only one of many factors that shape how consumers evaluate the fairness of a price. Other factors that were not included in the model, such as the absolute price level, perceived value for money, prior experience with dynamic pricing, or cultural attitudes toward price fluctuation, are likely to also play a role. Future research could incorporate these variables to provide a more complete picture of what drives fairness perception in algorithmic pricing contexts.

This finding also raises a broader conceptual question about the most relevant individual difference variable in algorithmic pricing contexts. In a study on recommender systems in U.S. e-commerce, Rainy and Dhanekula (2025) found that algorithm appreciation, which captures consumers' general attitude toward algorithmic guidance, was positively associated with both consumer trust ($M = 4.09$ for appreciators vs. 3.29 for averse consumers) and purchase intention ($M = 4.12$ vs. 3.52). Unlike AI literacy in the present study, which showed no correlation with any outcome variable, this attitudinal measure was consistently associated with key outcomes such as consumer trust and purchase intention. This suggests that what shapes consumer responses to algorithmic systems may be less about what consumers know about AI and more about how they feel toward it. Future research could explore whether algorithm appreciation or aversion moderates the effect of transparency on fairness more effectively than cognitive literacy.

6 Conclusion

The rapid adoption of artificial intelligence in the tourism industry has deeply transformed how online platforms operate, particularly in pricing. Algorithmic dynamic pricing, which adjusts prices in real time based on demand, user behavior and contextual data, has become a standard practice across major booking platforms. While this approach offers clear advantages in terms of revenue optimization, it also introduces a significant challenge: the opacity of AI-driven pricing mechanisms can generate uncertainty, suspicion and perceptions of unfairness among consumers. In this context, the present study aimed to answer the following research question: *How does AI transparency influence purchase intention in online tourism platforms?* This question was addressed by examining the sequential role of fairness perception and consumer trust in the relationship between AI transparency and purchase intention on online tourism platforms.

An experimental study was conducted to test this model. Participants were randomly assigned to one of two conditions: a low transparency condition, where only a vague notice was provided with no reference to AI or the factors driving the price and a high transparency condition, where a clear and simple explanation of the AI pricing process was given. All other elements of the booking scenario remained identical across conditions.

The results demonstrate that AI transparency does not directly influence purchase intention. Instead, its effect operates entirely through an indirect cognitive pathway. When consumers are provided with a clear explanation of how an AI system determines prices, they evaluate the pricing process as significantly fairer than when no such explanation is given. This enhanced fairness perception, in turn, strongly predicts consumer trust in the platform, which then drives purchase intention. The four hypotheses corresponding to this sequential chain (H1 through H4) were all empirically supported. Importantly, while the direct effect of transparency on purchase intention was non-significant, the indirect pathway through fairness and consumer trust was. This means that simply disclosing information is not sufficient to change consumer behavior. The explanation must first be cognitively processed as fair and translated into relational beliefs before it can shape purchase decisions.

The fifth hypothesis, which predicted that AI literacy would moderate the relationship between AI transparency and fairness perception, was not supported. Consumers with higher and lower levels of AI literacy responded similarly to the transparency manipulation. The most plausible explanation is that the transparency condition was formulated in plain and accessible language that did not require any technical knowledge to understand. As a result, all participants were able to process the explanation similarly, regardless of their familiarity with AI. This suggests that when AI transparency disclosures prioritize clarity over technical detail, they can be equally effective across all consumers.

From a theoretical standpoint, this study contributes to the literature by integrating AI transparency, fairness perception, consumer trust and purchase intention into a single tested sequential framework, whereas previous research had mostly examined these constructs separately or in pairs. The confirmation of an indirect-only mediation pattern clarifies how AI transparency influences consumer behavior in algorithmic pricing environments: not directly, but through the psychological states it activates. Furthermore, situating this framework in the online tourism context, where the intangibility of services and the irreversibility of bookings make consumer trust and fairness particularly relevant, extends the applicability of these findings beyond general e-commerce settings.

From a managerial perspective, the findings suggest that transparency should be treated as a trust-building strategy and not simply as a regulatory requirement. Online tourism platforms that explain clearly how their prices are set can benefit from stronger fairness perceptions and higher consumer trust, both of which predict purchase intention. Furthermore, since AI literacy does not moderate this relationship, a single clear and accessible explanation is sufficient to serve all consumers regardless of their level of AI knowledge.

Looking ahead, this research raises several questions for future investigation. The present study used only two levels of transparency (low and high). Future research could explore whether intermediate levels of disclosure produce different effects or whether there is a point beyond which too much information becomes counterproductive. The null finding on AI literacy suggests that cognitive knowledge about AI may not be the most relevant individual difference in this context. Future research could examine whether attitudinal dispositions toward AI, such as algorithm aversion or technology anxiety, play a stronger moderating role in shaping consumer responses to algorithmic pricing. Finally, it would be valuable to examine whether the mechanisms identified in this study generalize to other contexts (such as e-commerce, ridesharing or entertainment), where the nature of the product and the consumer's relationship to the platform differ significantly.

In conclusion, this study demonstrates that in the context of AI-driven dynamic pricing in online tourism, transparency matters. However, it does not directly persuade consumers to purchase. Rather, it initiates a cognitive process through which consumers evaluate the fairness of the pricing system, develop trust in the platform and ultimately form their purchase intention. Explaining how prices are determined is therefore not only an ethical obligation but a strategic mechanism through which online tourism platforms can strengthen consumer trust and influence purchase decisions.

7 Appendices

7.1 Appendix A - Experimental stimuli

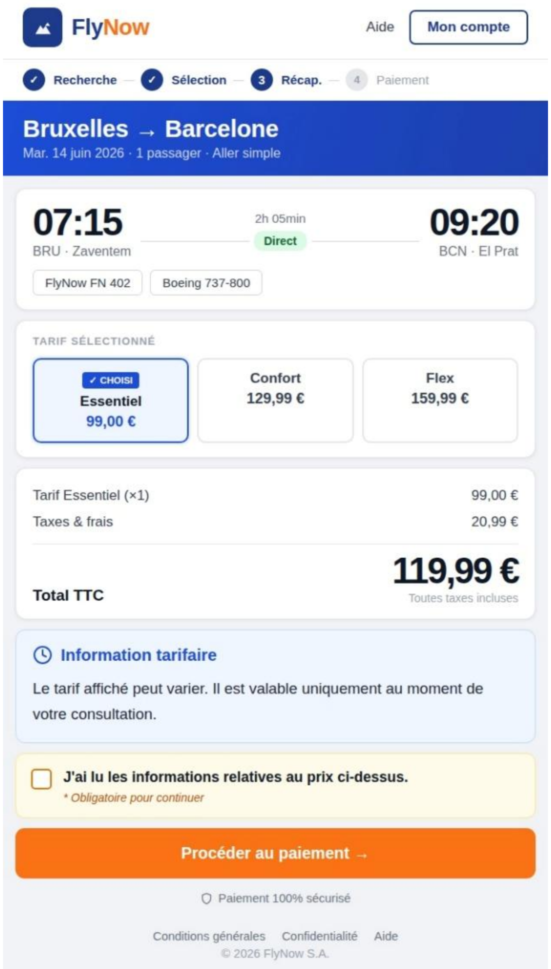


Figure A1. *FlyNow booking page: Condition A (Low Transparency), French version*

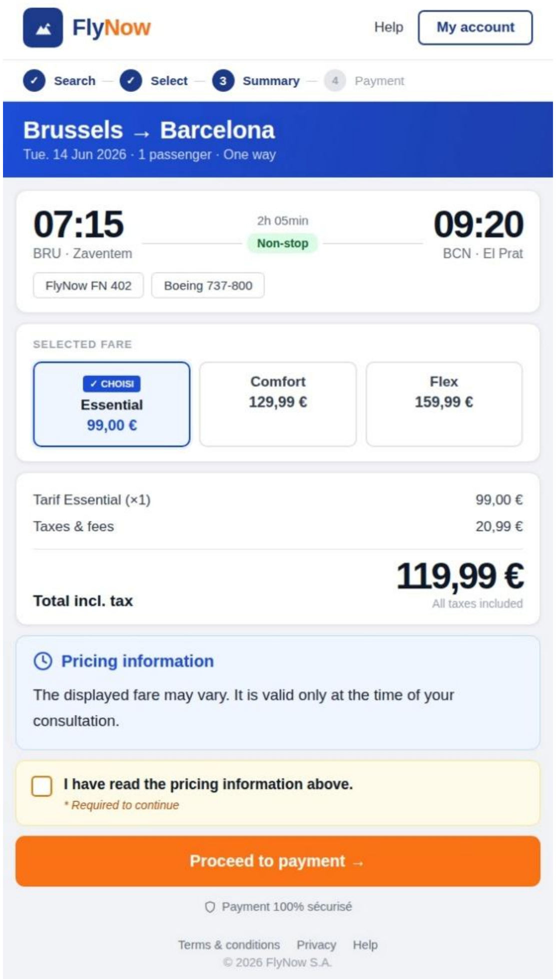


Figure A2. *FlyNow booking page: Condition A (Low Transparency), English version*

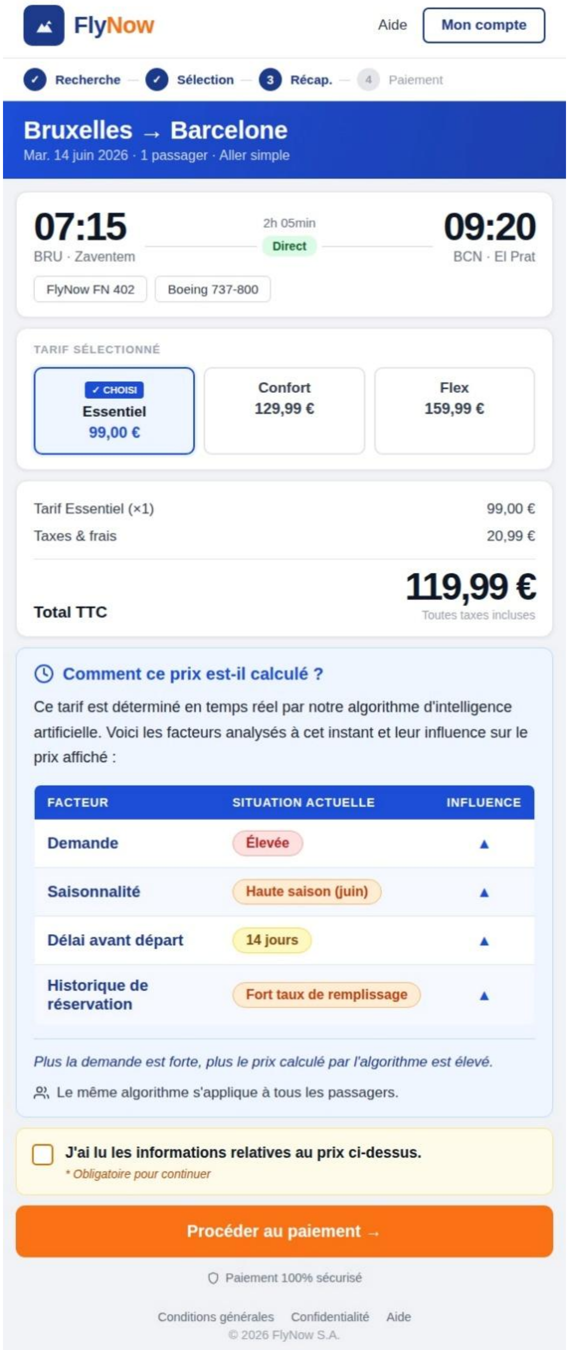


Figure A3. *FlyNow booking page: Condition B (High Transparency), French version*

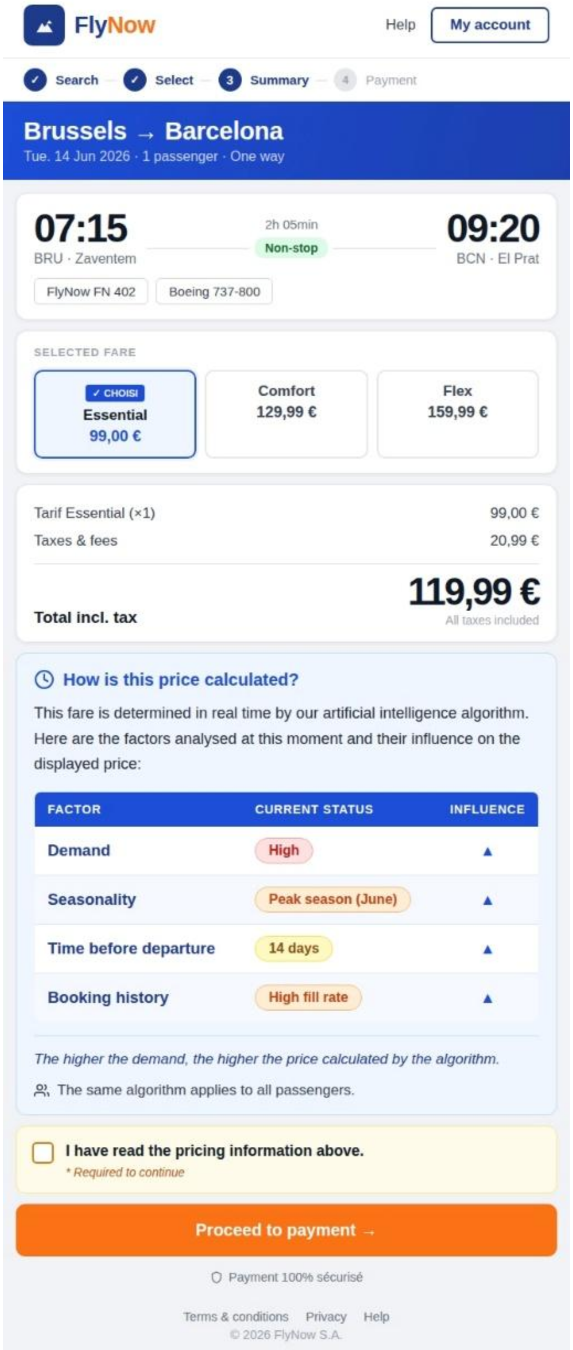


Figure A4. *FlyNow booking page: Condition B (High Transparency), English version*

7.2 Appendix B - Recruitment material

Figure B1. *Recruitment poster: Physical and online distribution*

Vous avez déjà réservé un vol en ligne ?✈️
👉Alors, votre avis m'intéresse !

Dans le cadre de mon mémoire de Master à HEC Liège, je réalise une étude sur la réservation de vols en ligne et le ressenti des utilisateurs. 🔍

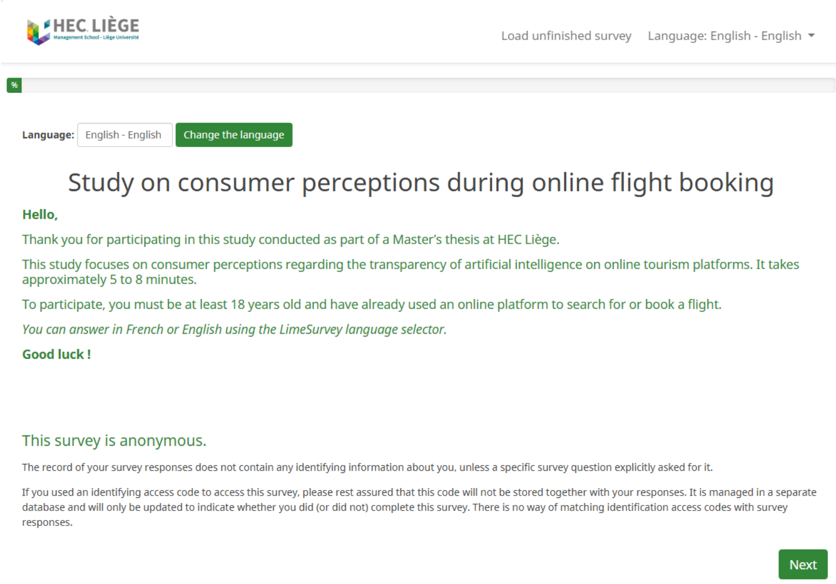
💬 Le questionnaire est anonyme et ne prend que 5 minutes.

Votre aide me serait vraiment précieuse.
Merci beaucoup pour votre participation et pour tout partage !😊

Figure B2. *Social media caption: Facebook and LinkedIn*

7.3 Appendix C - Survey questionnaire (LimeSurvey)

Note. The questionnaire was administered in both French and English. The English version is presented below. The French version followed an identical structure and item order.



HEC LIÈGE

Load unfinished survey Language: English - English

Language: English - English Change the language

Study on consumer perceptions during online flight booking

Hello,

Thank you for participating in this study conducted as part of a Master's thesis at HEC Liège.

This study focuses on consumer perceptions regarding the transparency of artificial intelligence on online tourism platforms. It takes approximately 5 to 8 minutes.

To participate, you must be at least 18 years old and have already used an online platform to search for or book a flight.

You can answer in French or English using the LimeSurvey language selector.

Good luck !

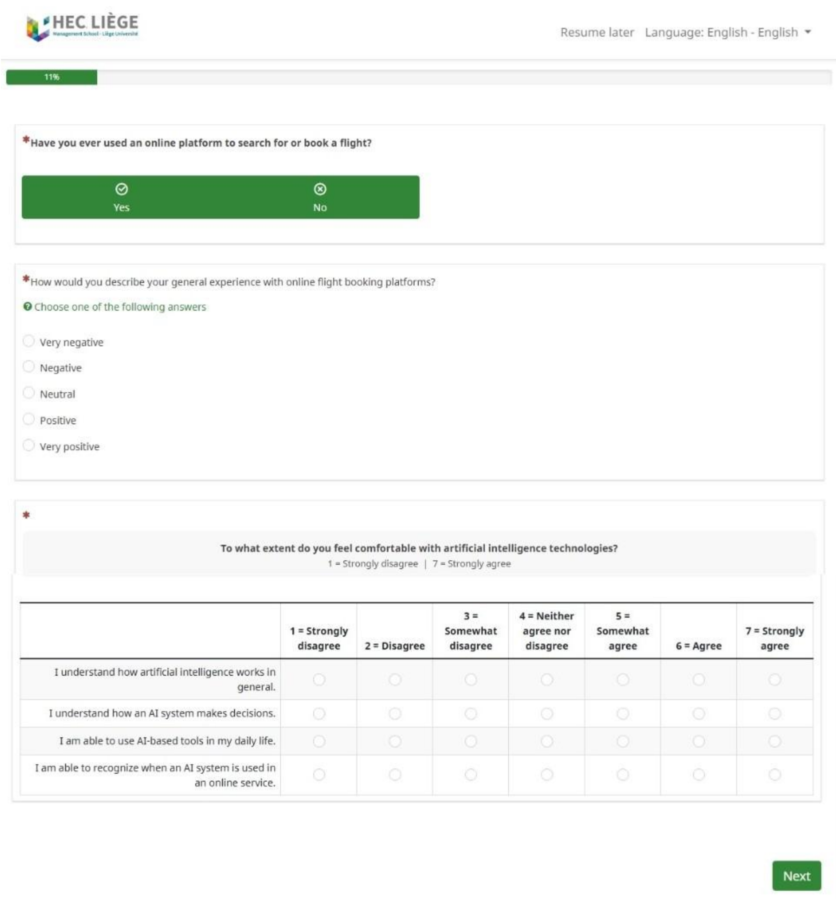
This survey is anonymous.

The record of your survey responses does not contain any identifying information about you, unless a specific survey question explicitly asked for it.

If you used an identifying access code to access this survey, please rest assured that this code will not be stored together with your responses. It is managed in a separate database and will only be updated to indicate whether you did (or did not) complete this survey. There is no way of matching identification access codes with survey responses.

Next

Figure C1. *Introduction page and language selection*



HEC LIÈGE

Resume later Language: English - English

11%

*Have you ever used an online platform to search for or book a flight?

Yes No

*How would you describe your general experience with online flight booking platforms?

Choose one of the following answers

- Very negative
- Negative
- Neutral
- Positive
- Very positive

*

To what extent do you feel comfortable with artificial intelligence technologies?

1 = Strongly disagree | 7 = Strongly agree

	1 = Strongly disagree	2 = Disagree	3 = Somewhat disagree	4 = Neither agree nor disagree	5 = Somewhat agree	6 = Agree	7 = Strongly agree
I understand how artificial intelligence works in general.							
I understand how an AI system makes decisions.							
I am able to use AI-based tools in my daily life.							
I am able to recognize when an AI system is used in an online service.							

Next

Figure C2. *Screening question, general experience and AI Literacy scale (AIL1–AIL4)*

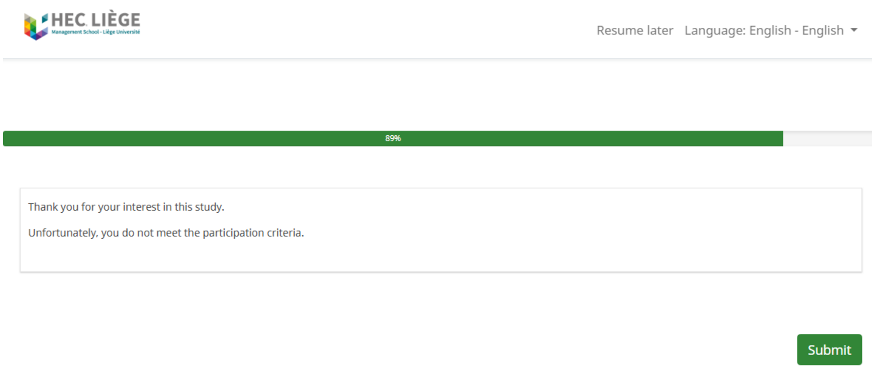


Figure C3. *Screen-out page: Ineligible participants*

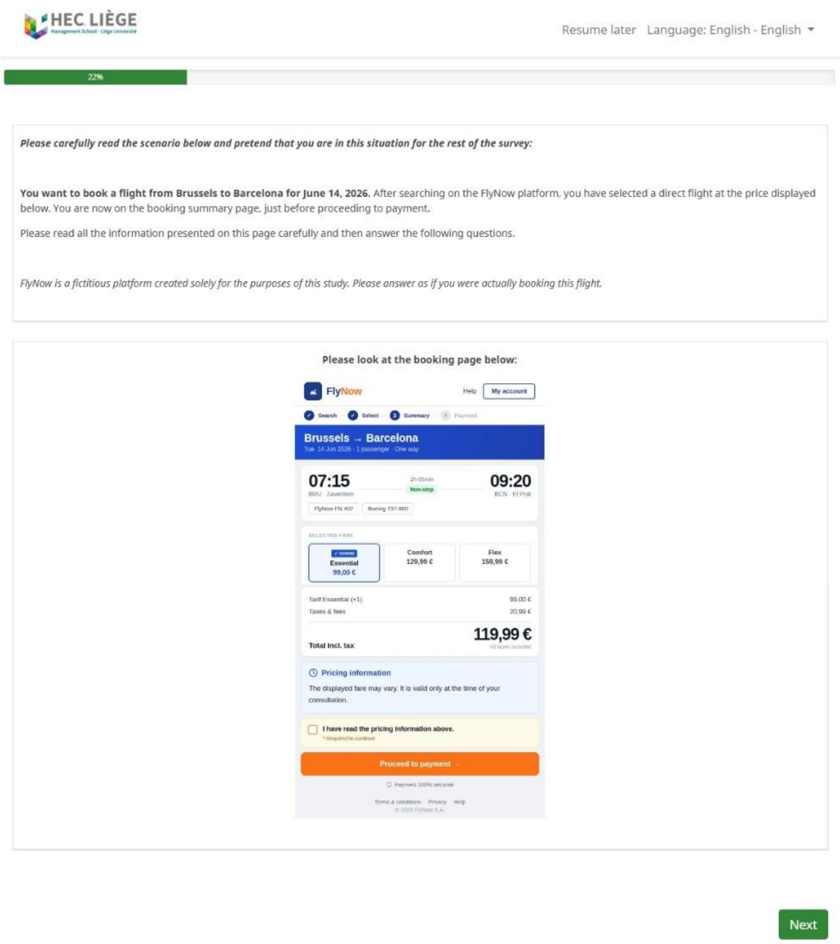
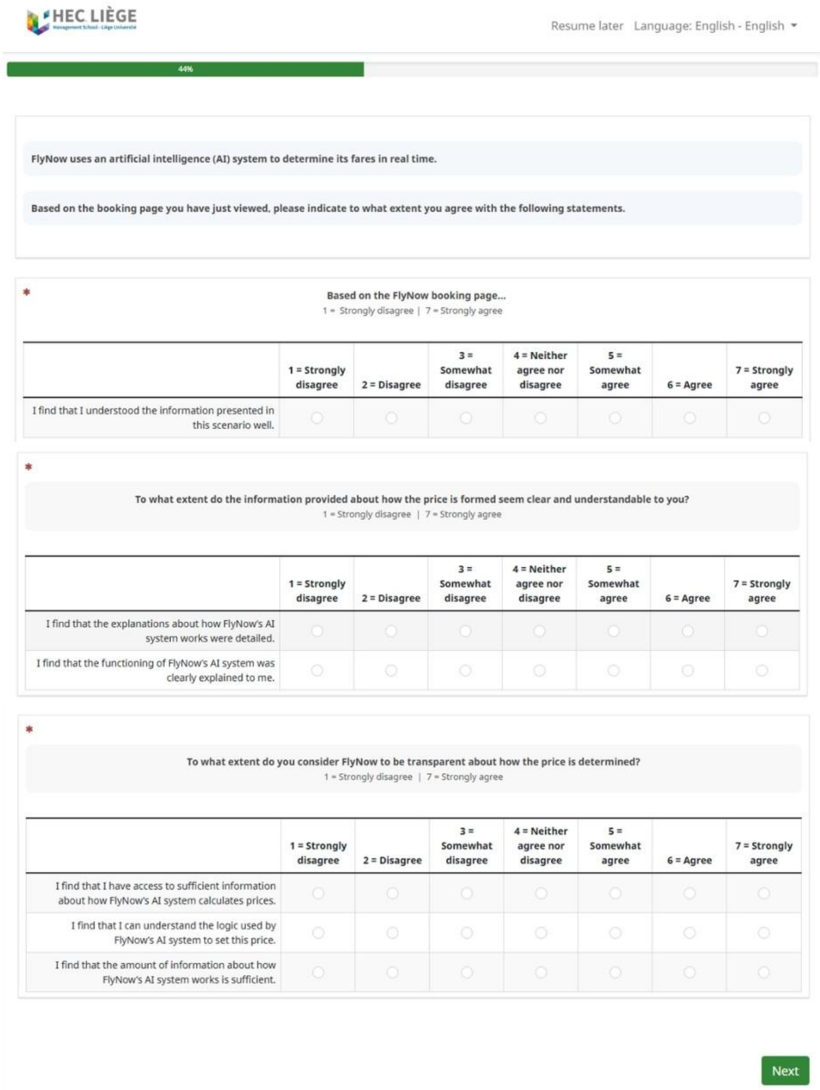


Figure C4. *Experimental scenario: Condition A (Low Transparency)*
Note. Only Condition A is shown. See Appendix A for both conditions.


HEC LIÈGE

Resume later Language: English - English

44%

FlyNow uses an artificial intelligence (AI) system to determine its fares in real time.

Based on the booking page you have just viewed, please indicate to what extent you agree with the following statements.

* Based on the FlyNow booking page...

1 = Strongly disagree | 7 = Strongly agree

	1 = Strongly disagree	2 = Disagree	3 = Somewhat disagree	4 = Neither agree nor disagree	5 = Somewhat agree	6 = Agree	7 = Strongly agree
I find that I understood the information presented in this scenario well.	○	○	○	○	○	○	○

* To what extent do the information provided about how the price is formed seem clear and understandable to you?

1 = Strongly disagree | 7 = Strongly agree

	1 = Strongly disagree	2 = Disagree	3 = Somewhat disagree	4 = Neither agree nor disagree	5 = Somewhat agree	6 = Agree	7 = Strongly agree
I find that the explanations about how FlyNow's AI system works were detailed.	○	○	○	○	○	○	○
I find that the functioning of FlyNow's AI system was clearly explained to me.	○	○	○	○	○	○	○

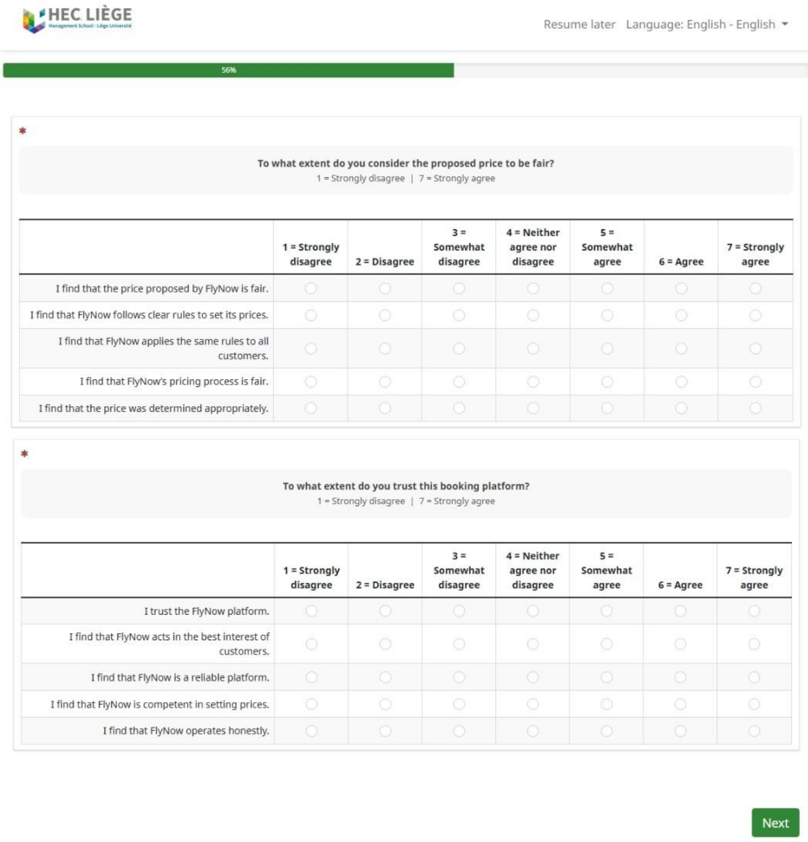
* To what extent do you consider FlyNow to be transparent about how the price is determined?

1 = Strongly disagree | 7 = Strongly agree

	1 = Strongly disagree	2 = Disagree	3 = Somewhat disagree	4 = Neither agree nor disagree	5 = Somewhat agree	6 = Agree	7 = Strongly agree
I find that I have access to sufficient information about how FlyNow's AI system calculates prices.	○	○	○	○	○	○	○
I find that I can understand the logic used by FlyNow's AI system to set this price.	○	○	○	○	○	○	○
I find that the amount of information about how FlyNow's AI system works is sufficient.	○	○	○	○	○	○	○

Next

Figure C5. *Transition statement, comprehension check (CC1), manipulation check (MC1–MC2) and AI Transparency scale (AIT1–AIT3)*



HEC LIÈGE
Management School - Liège Université

Resume later Language: English - English

56%

*

To what extent do you consider the proposed price to be fair?
1 = Strongly disagree | 7 = Strongly agree

	1 = Strongly disagree	2 = Disagree	3 = Somewhat disagree	4 = Neither agree nor disagree	5 = Somewhat agree	6 = Agree	7 = Strongly agree
I find that the price proposed by FlyNow is fair.							
I find that FlyNow follows clear rules to set its prices.							
I find that FlyNow applies the same rules to all customers.							
I find that FlyNow's pricing process is fair.							
I find that the price was determined appropriately.							

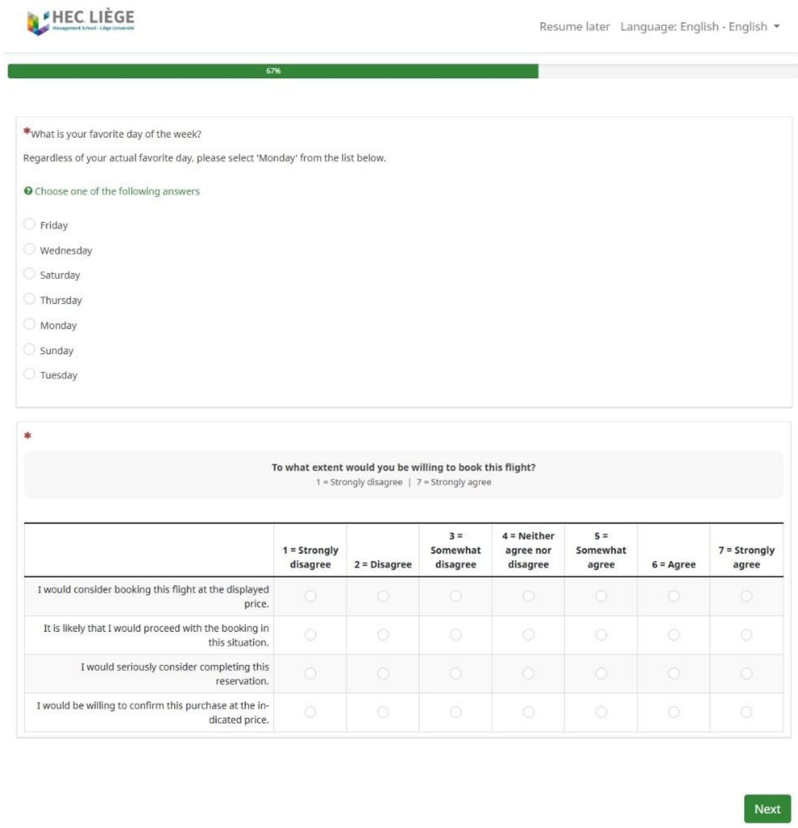
*

To what extent do you trust this booking platform?
1 = Strongly disagree | 7 = Strongly agree

	1 = Strongly disagree	2 = Disagree	3 = Somewhat disagree	4 = Neither agree nor disagree	5 = Somewhat agree	6 = Agree	7 = Strongly agree
I trust the FlyNow platform.							
I find that FlyNow acts in the best interest of customers.							
I find that FlyNow is a reliable platform.							
I find that FlyNow is competent in setting prices.							
I find that FlyNow operates honestly.							

Next

Figure C6. *Fairness Perception (FP1–FP5) and Consumer Trust (CT1–CT5)*



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67%

*What is your favorite day of the week?

Regardless of your actual favorite day, please select 'Monday' from the list below.

Choose one of the following answers

- Friday
- Wednesday
- Saturday
- Thursday
- Monday
- Sunday
- Tuesday

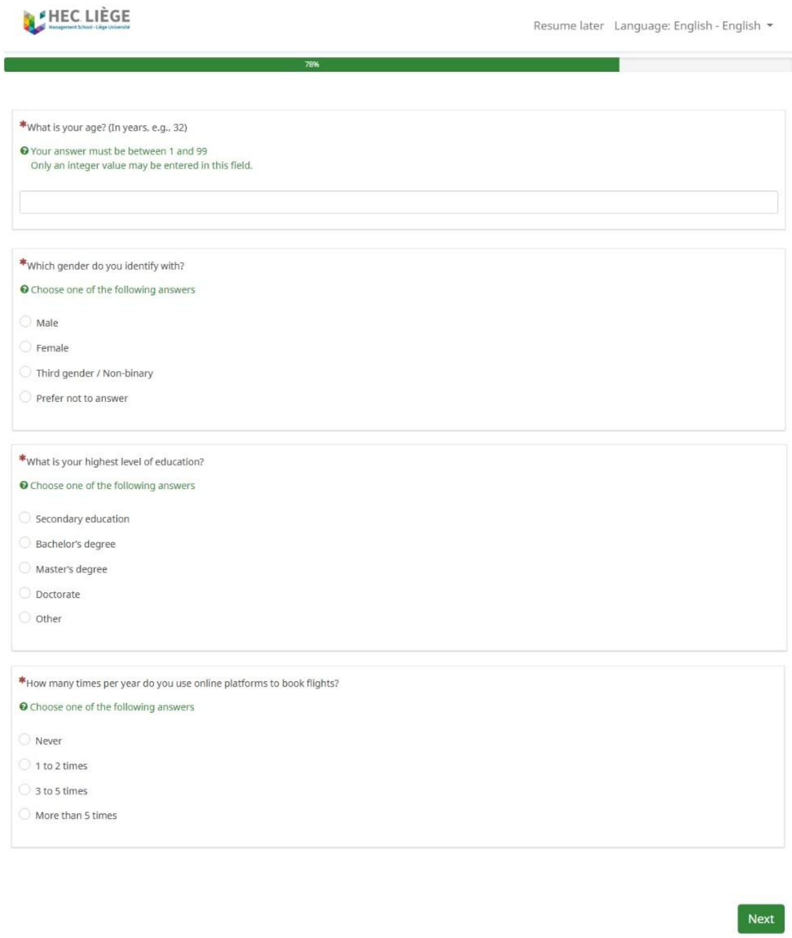
*

To what extent would you be willing to book this flight?
1 = Strongly disagree | 7 = Strongly agree

	1 = Strongly disagree	2 = Disagree	3 = Somewhat disagree	4 = Neither agree nor disagree	5 = Somewhat agree	6 = Agree	7 = Strongly agree
I would consider booking this flight at the displayed price.							
It is likely that I would proceed with the booking in this situation.							
I would seriously consider completing this reservation.							
I would be willing to confirm this purchase at the indicated price.							

Next

Figure C7. *Attention check and Purchase Intention (PI1–PI4)*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78%

*What is your age? (In years, e.g., 32)

Your answer must be between 1 and 99

Only an integer value may be entered in this field.

*Which gender do you identify with?

Choose one of the following answers

- Male
- Female
- Third gender / Non-binary
- Prefer not to answer

*What is your highest level of education?

Choose one of the following answers

- Secondary education
- Bachelor's degree
- Master's degree
- Doctorate
- Other

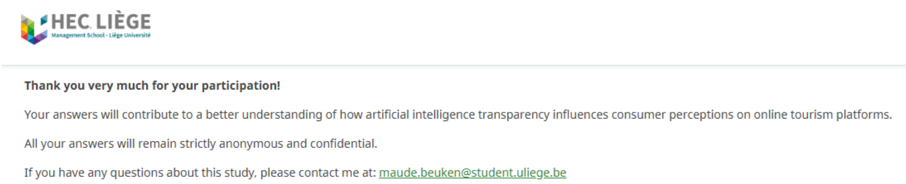
*How many times per year do you use online platforms to book flights?

Choose one of the following answers

- Never
- 1 to 2 times
- 3 to 5 times
- More than 5 times

Next

Figure C8. *Demographic questions (D1–D4)*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Thank you very much for your participation!

Your answers will contribute to a better understanding of how artificial intelligence transparency influences consumer perceptions on online tourism platforms.

All your answers will remain strictly anonymous and confidential.

If you have any questions about this study, please contact me at: maude.beuken@student.uliege.be

Figure C9. *End page: Thank you message*

7.4 Appendix D - JASP statistical outputs

7.4.1 Descriptive statistics and group equivalence

Table D1. *Frequency table: Education*

Frequencies for education ▼

education	Frequency	Percent	Valid Percent	Cumulative Percent
Bachelor's degree	56	42.7	42.7	42.7
Doctorate	1	0.8	0.8	43.5
Master's degree	57	43.5	43.5	87.0
Other	1	0.8	0.8	87.8
Secondary education	16	12.2	12.2	100.0
Missing	0	0.0		
Total	131	100.0		

Table D2. *Frequency table: Gender*

Frequencies for gender

gender	Frequency	Percent	Valid Percent	Cumulative Percent
Female	82	62.6	62.6	62.6
Male	48	36.6	36.6	99.2
Prefer not to answer	1	0.8	0.8	100.0
Missing	0	0.0		
Total	131	100.0		

Table D3. *Frequency table: Booking frequency*

Frequencies for booking_frequency

booking_frequency	Frequency	Percent	Valid Percent	Cumulative Percent
1 to 2 times	92	70.2	70.2	70.2
3 to 5 times	18	13.7	13.7	84.0
More than 5 times	14	10.7	10.7	94.7
Never	7	5.3	5.3	100.0
Missing	0	0.0		
Total	131	100.0		

Table D4. *Frequency table: Condition*

Frequencies for condition

condition	Frequency	Percent	Valid Percent	Cumulative Percent
A_Low_Transparency	70	53.4	53.4	53.4
B_High_Transparency	61	46.6	46.6	100.0
Missing	0	0.0		
Total	131	100.0		

Table D5. Independent samples t-test and *group descriptives: Age by condition*

Independent Samples T-Test

	Test	Statistic	df	p	Cohen's d	SE Cohen's d	95% CI for Cohen's d Lower	95% CI for Cohen's d Upper
age	Student	−2.150	129.0	.033	−0.377	0.178	−0.722	−0.029
	Welch	−2.103	107.1	.038	−0.372	0.178	−0.718	−0.025

Group Descriptives

	Group	N	Mean	SD	SE	Coefficient of variation
age	0	70	30.36	13.25	1.583	0.436
	1	61	36.34	18.48	2.367	0.509

Table D6. *Contingency table and Chi-squared test: Gender × Condition*

Contingency Tables ▼

	condition		
gender	A_Low_Transparency	B_High_Transparency	Total
Female	46	36	82
Male	24	24	48
Prefer not to answer	0	1	1
Total	70	61	131

Note. Each cell displays the observed counts

Chi-Squared Tests ▼

	Value	df	p
X^2	1.609	2	.447
N	131		

Note. Continuity correction is available only for 2x2 tables.

Table D7. *Contingency table and Chi-squared test: Education × Condition*

Contingency Tables

	condition		
education	A_Low_Transparency	B_High_Transparency	Total
Bachelor's degree	26	30	56
Doctorate	1	0	1
Master's degree	35	22	57
Other	1	0	1
Secondary education	7	9	16
Total	70	61	131

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	4.905	4	.297
N	131		

Note. Continuity correction is available only for 2x2 tables.

Table D8. *Contingency table and Chi-squared test: Booking frequency × Condition*

Contingency Tables

	condition		
booking_frequency	A_Low_Transparency	B_High_Transparency	Total
1 to 2 times	45	47	92
3 to 5 times	13	5	18
More than 5 times	10	4	14
Never	2	5	7
Total	70	61	131

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	6.870	3	.076
N	131		

Note. Continuity correction is available only for 2x2 tables.

7.4.2 Reliability analysis (Cronbach's Alpha)

Table D9. *Cronbach's Alpha: AI Literacy (AIL1–AIL4)*

Frequentist Scale Reliability Statistics

			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Cronbach's α	0.679	0.059	0.562	0.795

Frequentist Individual Item Reliability Statistics

	Cronbach's α (if item dropped)			Item-rest correlation		
Item	Estimate	Lower 95% CI	Upper 95% CI	Estimate	Lower 95% CI	Upper 95% CI
AIL1	0.562	0.401	0.722	0.571	0.443	0.677
AIL2	0.597	0.424	0.770	0.486	0.343	0.607
AIL3	0.590	0.418	0.763	0.498	0.357	0.617
AIL4	0.703	0.566	0.841	0.339	0.178	0.482

Table D10. *Cronbach's Alpha: Manipulation Check (MC1–MC2)*

Frequentist Scale Reliability Statistics

			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Cronbach's α	0.728	0.057	0.616	0.840

Frequentist Individual Item Reliability Statistics

	Cronbach's α (if item dropped)			Item-rest correlation		
Item	Estimate	Lower 95% CI	Upper 95% CI	Estimate	Lower 95% CI	Upper 95% CI
MC1				0.578	0.451	0.682
MC2				0.578	0.451	0.682

Note. Please enter at least 3 variables for the if item dropped statistics.

Table D11. *Cronbach's Alpha: AI Transparency (AIT1–AIT3)*

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Cronbach's α	0.876	0.023	0.830	0.921

Frequentist Individual Item Reliability Statistics ▼

	Cronbach's α (if item dropped)			Item-rest correlation		
Item	Estimate	Lower 95% CI	Upper 95% CI	Estimate	Lower 95% CI	Upper 95% CI
AIT1	0.766	0.661	0.870	0.824	0.759	0.872
AIT2	0.811	0.731	0.891	0.776	0.697	0.836
AIT3	0.885	0.841	0.929	0.691	0.589	0.771

Table D12. *Cronbach's Alpha: Fairness Perception (FP1–FP5)*

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Cronbach's α	0.897	0.016	0.866	0.927

Frequentist Individual Item Reliability Statistics

	Cronbach's α (if item dropped)			Item-rest correlation		
Item	Estimate	Lower 95% CI	Upper 95% CI	Estimate	Lower 95% CI	Upper 95% CI
FP1	0.916	0.888	0.945	0.522	0.385	0.636
FP2	0.872	0.832	0.913	0.753	0.668	0.819
FP3	0.883	0.848	0.917	0.710	0.613	0.785
FP4	0.844	0.796	0.892	0.872	0.824	0.908
FP5	0.842	0.793	0.891	0.881	0.836	0.914

Note. Omega item dropped statistics with CFA failed.

Table D13. *Cronbach's Alpha: Consumer Trust (CT1–CT5)*

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Cronbach's α	0.900	0.019	0.863	0.937

Frequentist Individual Item Reliability Statistics

	Cronbach's α (if item dropped)			Item-rest correlation		
Item	Estimate	Lower 95% CI	Upper 95% CI	Estimate	Lower 95% CI	Upper 95% CI
CT1	0.879	0.830	0.928	0.750	0.664	0.817
CT2	0.889	0.836	0.942	0.700	0.601	0.778
CT3	0.878	0.829	0.927	0.760	0.677	0.824
CT4	0.865	0.816	0.914	0.810	0.742	0.862
CT5	0.879	0.815	0.942	0.750	0.664	0.816

Table D14. *Cronbach's Alpha: Purchase Intention (PI1–PI4)*

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Cronbach's α	0.966	0.007	0.953	0.980

Frequentist Individual Item Reliability Statistics

	Cronbach's α (if item dropped)			Item-rest correlation		
Item	Estimate	Lower 95% CI	Upper 95% CI	Estimate	Lower 95% CI	Upper 95% CI
PI1	0.967	0.950	0.984	0.879	0.833	0.913
PI2	0.954	0.936	0.973	0.923	0.892	0.945
PI3	0.946	0.923	0.968	0.951	0.932	0.965
PI4	0.955	0.938	0.972	0.923	0.893	0.945

7.4.3 Correlation matrix

Table D15. *Pearson's correlation matrix: all variables*

Pearson's Correlations

Variable		AIL_mean	AIT_mean	FP_mean	CT_mean	PI_mean
1. AIL_mean	Pearson's r	—				
2. AIT_mean	Pearson's r	0.091	—			
3. FP_mean	Pearson's r	0.058	0.586***	—		
4. CT_mean	Pearson's r	−0.007	0.356***	0.714***	—	
5. PI_mean	Pearson's r	0.091	0.037	0.344***	0.603***	—

* p < .05, ** p < .01, *** p < .001

7.4.4 Hypothesis testing

Table D16. *Independent samples t-test: Manipulation check and H1 (MC_mean, AIT_mean, FP_mean)*

Independent Samples T-Test

	Test	Statistic	df	p	Cohen's d	SE Cohen's d	95% CI for Cohen's d Lower	95% CI for Cohen's d Upper
MC_mean	Student	−5.179	129.0	< .001	−0.907	0.191	−1.266	−0.545
	Welch	−5.243	128.8	< .001	−0.913	0.191	−1.272	−0.550
AIT_mean	Student	−7.929	129.0	< .001	−1.389	0.211	−1.769	−1.004
	Welch	−7.990	128.9	< .001	−1.394	0.211	−1.775	−1.009
FP_mean	Student	−2.908	129.0	.004	−0.509	0.180	−0.857	−0.160
	Welch	−2.909	126.8	.004	−0.509	0.180	−0.857	−0.160

Table D17. *Group descriptives by condition: Manipulation check and H1*

Group Descriptives

	Group	N	Mean	SD	SE	Coefficient of variation
MC_mean	0	70	3.736	1.348	0.161	0.361
	1	61	4.869	1.125	0.144	0.231
AIT_mean	0	70	3.071	1.194	0.143	0.389
	1	61	4.650	1.067	0.137	0.229
FP_mean	0	70	3.846	1.059	0.127	0.275
	1	61	4.384	1.052	0.135	0.240

Table D18. *Linear regression: H2 (Fairness Perception → Consumer Trust)*

Model Summary - CT_mean

Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	df1	df2	p
M_0	0.000	0.000	0.000	1.011	0.000	0	130	
M_1	0.714	0.510	0.506	0.711	0.510	1	129	< .001

Note. M_1 includes FP_mean

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	67.82	1	67.82	134.3	< .001
	Residual	65.17	129	0.505		
	Total	133.0	130			

Note. M_1 includes FP_mean

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

							95% CI	
Model		Unstandardized	Standard Error	Standardized	t	p	Lower	Upper
M_0	(Intercept)	3.901	0.088		44.14	< .001	3.726	4.076
M_1	(Intercept)	1.176	0.243		4.837	< .001	0.695	1.657
	FP_mean	0.665	0.057	0.714	11.59	< .001	0.552	0.779

Descriptives

	N	Mean	SD	SE
CT_mean	131	3.901	1.011	0.088
FP_mean	131	4.096	1.086	0.095

Table D19. *Linear regression: H3 (Consumer Trust → Purchase Intention)*

Model Summary - PI_mean

Model	R	R²	Adjusted R²	RMSE	R² Change	df1	df2	p
M_0	0.000	0.000	0.000	1.386	0.000	0	130	
M_1	0.603	0.363	0.358	1.110	0.363	1	129	< .001

Note. M_1 includes CT_mean

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	90.71	1	90.71	73.62	< .001
	Residual	159.0	129	1.232		
	Total	249.7	130			

Note. M_1 includes CT_mean

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

							95% CI	
Model		Unstandardized	Standard Error	Standardized	t	p	Lower	Upper
M_0	(Intercept)	4.380	0.121		36.17	< .001	4.140	4.619
M_1	(Intercept)	1.158	0.388		2.986	.003	0.391	1.925
	CT_mean	0.826	0.096	0.603	8.580	< .001	0.635	1.016

Descriptives

	N	Mean	SD	SE
PI_mean	131	4.380	1.386	0.121
CT_mean	131	3.901	1.011	0.088

Table D20. *Structural equation modeling: H4 (Sequential mediation)*

Model fit

				n(Parameters)		Baseline test		
	AIC	BIC	n(Observations)	Total	Free	χ^2	df	p
Model 1	1074	1100	131	9	9	0.000	0.000	.966

Note. Fitting the model resulted in warnings. Check the 'Show warnings' box in the Output Options to see the warnings. Estimator is ML. Information matrix is expected. Standard errors are standard.

R-Squared

	R^2
FP_mean	0.062
CT_mean	0.511
PI_mean	0.389

Regression coefficients

							95% Confidence Interval	
Outcome	Predictor		Std. estimate	Std. Error	z-value	p	Lower	Upper
CT_mean	FP_mean	a2	0.721	0.045	15.99	< .001	0.633	0.810
	condition_num	d	−0.029	0.063	−0.464	.643	−0.153	0.094
FP_mean	condition_num	a1	0.248	0.081	3.072	.002	0.090	0.406
PI_mean	CT_mean	b	0.723	0.085	8.531	< .001	0.557	0.890
	condition_num	cprime	−0.107	0.070	−1.527	.127	−0.244	0.030
	FP_mean	f	−0.147	0.099	−1.475	.140	−0.341	0.048

Residual variances

					95% Confidence Interval	
Variable	Std. estimate	Std. Error	z-value	p	Lower	Upper
FP_mean	0.938	0.040	23.44	< .001	0.860	1.017
CT_mean	0.489	0.061	8.009	< .001	0.369	0.609
PI_mean	0.611	0.067	9.170	< .001	0.480	0.741
condition_num	1.000	0.000			1.000	1.000

Defined parameters

					95% Confidence Interval	
Name	Std. estimate	Std. Error	z-value	p	Lower	Upper
indirect_serial	0.129	0.048	2.724	.006	0.036	0.223
direct	−0.107	0.070	−1.527	.127	−0.244	0.030
total	0.022	0.086	0.260	.795	−0.147	0.192

Table D21. *Linear regression with interaction: H5 (Moderation of AI Literacy)*

Model Summary - FP_mean

Model	R	R^2	Adjusted R^2	RMSE	R^2 Change	df1	df2	p
M_0	0.269	0.073	0.058	1.054	0.073	2	128	.008
M_1	0.269	0.073	0.051	1.058	0.000	1	127	.994

Note. M_0 includes condition_num, AIL_mean

Note. M_1 includes condition_num, AIL_mean, condition_num:AIL_mean

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_0	Regression	11.13	2	5.564	5.009	.008
	Residual	142.2	128	1.111		
	Total	153.3	130			
M_1	Regression	11.13	3	3.709	3.313	.022
	Residual	142.2	127	1.120		
	Total	153.3	130			

Note. M_0 includes condition_num, AIL_mean

Note. M_1 includes condition_num, AIL_mean, condition_num:AIL_mean

Coefficients

							95% CI	
Model		Unstandardized	Standard Error	Standardized	t	p	Lower	Upper
M_0	(Intercept)	3.168	0.563		5.627	< .001	2.054	4.282
	condition_num	0.580	0.188	0.268	3.090	.002	0.209	0.952
	AIL_mean	0.132	0.107	0.107	1.236	.219	−0.079	0.344
M_1	(Intercept)	3.172	0.862		3.681	< .001	1.467	4.877
	condition_num	0.573	1.104	0.264	0.519	.605	−1.612	2.757
	AIL_mean	0.131	0.166	0.106	0.790	.431	−0.197	0.460
	condition_num ✻ AIL_mean	0.002	0.218	0.003	0.007	.994	−0.429	0.432

8 List of resource persons

Name	***Role***	***Contribution***
Youssra El Midaoui	Supervisor HEC Liège	Regular meetings to discuss the development plan, intermediary report (for the literature review and conceptual framework) and methodology (for the experimentation stimuli and questionnaire on LimeSurvey).
Willem Standaert	Reader HEC Liège	Evaluation of the thesis and feedback on the final manuscript.

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EXECUTIVE SUMMARY

Tourism industry increasingly relies on artificial intelligence to optimize pricing. Algorithmic dynamic pricing, which adjusts prices in real time based on demand and user behavior, is now standard practice on platforms such as Booking.com and Expedia. However, the opacity of these AI-driven mechanisms generates consumer concerns about fairness and trustworthiness. Despite the growing adoption of such systems, limited research has examined how these constructs interact within a unified framework in tourism. This study aims to understand how AI transparency influences consumer purchase intention and to identify the underlying psychological mechanisms.

Drawing on procedural justice theory, price fairness literature, trust formation theory and AI transparency research, the study proposes a sequential mediation model: AI Transparency → Fairness Perception → Consumer Trust → Purchase Intention. AI literacy is also examined as a moderator of the transparency–fairness relationship.

An experiment was conducted where participants (N = 131) were randomly assigned to either a low- or high-transparency condition on a fictitious airline booking platform, FlyNow, with the price, flight details and booking interface held constant. Variables were measured using validated Likert-scale instruments.

The results support the proposed sequential mechanism. Higher transparency significantly improved fairness perception, which in turn strengthened consumer trust and increased purchase intention. Importantly, AI transparency doesn't directly persuade consumers to purchase. Rather, it initiates a cognitive chain in which fairness perception and trust fully mediate its influence on purchase intention. The moderating effect of AI literacy was not supported, suggesting that clear explanations are equally effective regardless of AI knowledge.

This study contributes to the literature by integrating these constructs into a single tested sequential framework within online tourism. For platform managers, findings demonstrate that AI transparency is not simply a regulatory obligation but a trust-building strategy: easily understandable pricing explanations can strengthen consumer trust and ultimately increase booking likelihood.

KEYWORDS: AI transparency, algorithmic dynamic pricing, online tourism, fairness perception, consumer trust, purchase intention, AI literacy

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