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The Limits of Disclosure

Does Pricing-Source Disclosure Influence Consumer Evaluations of Personalized Pricing?

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Abstract

This paper investigates how disclosure of AI- versus human-generated personalized pricing influences consumer evaluations of personalized pricing and retailers. Drawing on algorithm aversion literature, we examine whether dehumanization, procedural justice, and ulterior motives mediate these relationships, and whether subjective socioeconomic status (SES) moderates them. Using a scenario-based experiment with Swedish consumers (n = 289), participants were randomly assigned to receive either AI- or human-generated personalized pricing in an online retail context. Contrary to expectations, no significant differences emerged between conditions on satisfaction, retailer attitudes, or the proposed mediators. One possible explanation is that the study may have had limited statistical power to detect small effects, particularly due to insufficient number of participants. However, all three mediators were significantly associated with both outcomes in the expected directions. Exploratory findings further suggested that lower-SES consumers may experience stronger dehumanization responses to AI-driven pricing. Overall, the findings suggest that pricing-source disclosure alone may be insufficient to trigger negative consumer responses in familiar, low-stakes retail settings where AI systems have become increasingly normalized.

Keywords: algorithmic pricing; pricing-source disclosure; algorithmic aversion; dehumanization; procedural justice; ulterior motives; socioeconomic status; customer satisfaction; attitude; AI in retail

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1. Introduction

Personalized pricing – where retailers set prices based on individual consumer characteristics such as purchase history, browsing behavior, and demographics – has emerged as a prominent topic within both retail practice and academic discussion (Cao et al., 2021; Guha et al., 2021). Fueled by advances in artificial intelligence (AI), firms can now estimate customers' willingness to pay (Bar-Gill, 2019) and adjust prices accordingly to boost sales or maximize profits (Cao et al., 2021). As stated by Libai et al. (2020), AI is fundamentally reshaping how firms manage customer relationships, creating new opportunities for algorithmic and personalized pricing practices in retail environments. Building on this, Seele et al. (2021), define this as algorithmic pricing, allowing firms to "automatically generate dynamic and customer-specific prices in real-time".

However, these advancements have been accompanied by considerable criticism. For instance, the Apple Card case raised serious concerns about algorithmic gender bias after a user discovered that his wife had been offered a credit limit twenty times lower than his own despite having a higher credit score (Mills, 2019). Beyond individual cases, scholars have warned that AI systems may intensify firms' ability to engage in personalized price discrimination and exploit informational asymmetries between firms and customers (Gasser & Almeida, 2017). Despite such concerns, pricing decisions previously made by humans are increasingly delegated to algorithms (Calvano et al., 2019),

Beyond its managerial relevance, personalized pricing has attracted increasing regulatory attention. Existing legal frameworks, including consumer protection law, competition law, and General Data Protection Regulation (GDPR), provide some oversight of algorithmic pricing practices. However, scholars have questioned whether these frameworks are sufficient. For example, Li (2022) argues that certain forms of algorithmic pricing are "highly likely to bypass the GDPR in reality", by relying on affinity or anonymous data rather than identifiable personal data.

In response to such challenges, the European Union has introduced the Omnibus Directive. This directive requires online traders to inform consumers when prices are personalized on the basis of automated decision-making (Directive 2019/2161). The Digital Services Act has strengthened transparency and accountability obligations for online platforms (Regulation

2022/2065). Together, these developments suggest that disclosure of personalized pricing is increasingly becoming a legal requirement.

Given that algorithms increase the ability to engage in price discrimination (Bar-Gill, 2019),surprisingly little is known about how different consumer groups respond to the disclosed source behind these decisions. Existing literature has largely examined personalized pricing through the lenses of ethical concerns and perceived fairness (Seele et al., 2021), while giving limited attention to how customers' social background influences these responses. Yet, if algorithmic pricing raises concerns of discrimination experienced by consumers, it becomes important to understand whether these perceptions differ systematically across consumer groups. Consequently, several scholars have called for greater research into how individual characteristics and sociocultural factors shape responses to AI-driven decision-making and personalized pricing (Ohlwein & Bruno, 2025; Puntoni et al., 2021; Van der Rest et al., 2020).

1.2 Purpose and aim

The purpose of this thesis is to contribute to understanding consumer responses to algorithmic pricing by examining whether disclosure of AI involvement triggers negative evaluations compared to human-generated pricing when the price is already presented as personalized. Our goal is to examine consumer perceptions of this practice through dehumanization, procedural justice and ulterior motives and whether this is influenced by who they think is responsible for setting the price. In doing so, the study focuses specifically on the disclosed source of the pricing decision, rather than comparing personalized pricing with uniform pricing.

The aim is to test whether AI- versus human-generated personalized pricing disclosure affects consumer satisfaction and attitudes toward the retailer, and whether these effects are mediated by dehumanization, procedural justice, and ulterior motives and moderated by subjective socioeconomic status.

2. Theory and Hypothesis Development

2.1 Algorithm Aversion & Algorithm Appreciation

That individuals are hesitant to rely on algorithms is not a new insight (Dawes, 1979). More recently, Dietvorst, et al. (2015) conceptualized this phenomenon as *algorithm aversion*, describing the tendency to reject algorithmic decisions or advice in favor of human judgment, even when algorithms objectively perform better (Turel & Kalhan, 2023). This reluctance is particularly pronounced after observing algorithmic errors, leading individuals to systematically distrust algorithmic recommendations (Dietvorst et al., 2015; Prahl & Van Swol, 2017). Research in retail contexts has made similar observations. For example, Luo et al. (2019) found that consumers reacted less favorably to algorithmic agents when their use was explicitly disclosed, despite the agents outperforming human employees in terms of objective service outcomes – particularly in relational and advice-based service contexts. As firms increasingly leverage data to optimize core retail functions such as customer service, personalized marketing and logistics (Cao, 2021; Huang & Rust, 2021; Shankar, 2018; Guha et al., 2021), understanding the conditions under which aversion to algorithms emerges becomes increasingly important.

However, consumers do not respond uniformly to AI in retail settings. Emerging research suggests that algorithmic decision-making may in some contexts be positively received. Logg et al. (2019), for instance, demonstrated that individuals may in some situations rely more heavily on algorithms than humans – a phenomenon termed *algorithm appreciation*. Such appreciation is more likely to emerge when tasks are perceived as objective, analytical, and data-driven, where the rule-based and consistent nature of algorithms is viewed as advantageous (Castelo et al., 2019). More broadly, reactions towards algorithmic decision-making appear to depend substantially on contextual factors, including task type, perceived objectivity, and the social implication associated with decision (Castelo et al., 2019; Lee, 2018; Mahmud et al., 2021).

The distinction between aversion and appreciation is particularly relevant in the context of algorithmic pricing. On one hand, such pricing decisions are inherently quantitative and data-driven, potentially making algorithmic systems appear more objective, consistent, and capable of processing large amounts of consumer and market information (Castelo et al., 2019; Logg et al., 2019). On the other hand, the personal data used in such consumer characteristics – purchase history, browsing behavior, and demographics – enables pricing discrimination with highly differentiated outcomes from consumer to consumer (Guha et al., 2021; Seele et al., 2021; Priester et al., 2020). Unlike algorithmic recommendations, where the algorithm is experienced as acting in the consumer's interest, personalized pricing is experienced as the algorithm acting on behalf of the firm, identifying and extracting individual willingness to pay (Bar-Gill, 2019).

Thus, algorithmic pricing differs from other algorithmic decision contexts because consumers directly bear the financial consequences of the decision through the price they are asked to pay. Importantly, prior pricing literature consistently shows that consumers react negatively when firms use pricing mechanisms perceived as exploiting differences in willingness to pay or maximizing profit at the consumer's expense (Campbell, 1999; Bolton et al., 2003), and that algorithmic pricing often is associated with such activities (Ohlwein & Bruno, 2025). Further, the opaque nature of algorithms and the use of personal data mean that consumers interpret algorithmic prices through social and psychological lenses related to fairness and firm intention (Campbell, 1999; Priester et al., 2020; Wu et al., 2012). In such contexts, the objective and data-driven advantages associated with algorithmic systems may become outweighed by concerns regarding exploitation and unequal treatment.

Critically, rather than receiving a universally applied price, customers are individually targeted based on their estimated willingness to pay (Bar-Gill, 2019). This targeting logic makes personalized pricing socially sensitive and more comparable to the subjective decision contexts in which algorithm aversion tends to emerge (Castelo et al., 2019). In such a context, consumers may not only evaluate the pricing outcome, but also the source responsible for generating it to evaluate the process. Thus, AI versus human pricing source serves as the primary psychological cue for evaluating the process. Therefore, we hypothesize that:

H1a: *Pricing source (AI vs human) affects perceived satisfaction, meaning that AI-generated pricing disclosure leads to lower perceived satisfaction than human-generated pricing disclosure.*

Beyond the immediate evaluation of the pricing process, the disclosed use of AI may also shape consumers' broader evaluation of the retailer behind the decision. If AI-generated personalized pricing is interpreted as exploitative, opaque, or firm-serving (Campbell, 1999;

Wu et al., 2012), this may not only reduce satisfaction with the pricing process, but also contribute to less favorable evaluations of the retailer overall.

H1b: *Pricing source (AI vs human) affects perceived attitude towards the retailer, meaning that AI-generated pricing disclosure leads to lower perceived attitudes towards the retailer than human-generated pricing disclosure.*

2.2 Regulatory Context of Personalized Pricing Disclosure

The regulatory landscape surrounding personalized pricing in the European Union has made disclosure increasingly relevant for both firms and consumers. In particular, the Omnibus Directive (Directive (EU) 2019/2161) amended the Consumer Rights Directive (2011/83/EU) by requiring traders to inform consumers when a price has been personalized on the basis of automated decision-making. This means that, in the EU context, disclosure of personalized pricing is not only a managerial or strategic choice, but increasingly a legal requirement. As a result, understanding how consumers respond to such disclosures becomes important both theoretically and managerially.

In addition, the Digital Services Act (Regulation (EU) 2022/2065) introduces broader transparency obligations for online platforms, including requirements related to the main parameters used in recommender systems and restrictions on deceptive interface designs, often referred to as dark patterns. Although the DSA does not regulate personalized pricing as directly as the Omnibus Directive, it reflects a broader regulatory movement toward greater transparency and accountability in digital environments. Together, these developments strengthen the relevance of examining whether disclosure itself influences consumer evaluations of AI-driven personalized pricing.

2.3 Underlying Psychological Mechanisms

Anchored in algorithm aversion literature, this thesis examines the psychological mechanisms underlying consumer responses to AI-driven personalized pricing. In these contexts, consumer responses are shaped not only by the objective outcome itself, but also by how individuals psychologically interpret and experience the decision-making process (Puntoni et al., 2021). Hence, we propose that pricing-source disclosure may activate three related but distinct psychological mechanisms capturing interpersonal, procedural, and intentional dimensions of consumer evaluation – each reflecting a distinct lens through which consumers may question how they were treated, whether the pricing process was legitimate, and whether the firm's intentions were exploitative.

First, delegating pricing decisions to algorithms may reduce the emotional nuance associated with human judgment, potentially leading consumers to feel reduced to data points rather than recognized as individuals (Schultz et al., 2025; Turel & Kalhan, 2023). This interpersonal dimension is captured through perceptions of *dehumanization.* Second, because consumers evaluate not only pricing outcomes but also the fairness and legitimacy of the process through which prices are determined (Haws & Bearden, 2006; Van den Bos et al., 1997), perceptions of *procedural justice* become relevant. Third, consumers may infer underlying intentions behind personalized pricing practices, particularly when personal data is involved, making perceptions of *ulterior motives* central to understanding how consumers interpret firms' intentions and potential profit-seeking behavior (Campbell, 1999; Priester et al., 2020). Finally, subjective socioeconomic status (SES) is introduced as a moderating condition, given emerging evidence that individuals' perceived social position may shape how they interpret and respond to algorithmic decisions (Ohlwein & Bruno, 2025; Puntoni et al., 2021; Van der Rest et al., 2020). Each mechanism is discussed in turn in the following sections.

2.4 Dehumanization

As pricing decisions are increasingly delegated to algorithms rather than humans (Calvano et al., 2019), consumers are evaluated based on behavioral and demographic data rather than individual circumstance (Schultz et al., 2025). We propose that AI-generated pricing may trigger dehumanization – defined as the perception of being treated as less than fully human (Haslam & Stratemeyer, 2016) – and that this perception carries meaningful consequences for how consumers evaluate both the pricing process and the retailer behind it.

The psychological mechanism is rooted in what Waytz and Schroeder (2014) term dehumanization by omission, a passive process in which individuals are not fully recognized in their human individuality. Building on this logic, Schultz et al. (2025) argue that algorithmic systems may unintentionally dehumanize individuals by reducing them to behavioral patterns and demographic categories, treating consumers as data points rather than nuanced human beings (Bolin & Andersson Schwarz, 2015; Ghasemaghaei & Turel, 2025).

We focus in particular on consumers' subjective experience of this reduction. Kteily et al., (2016) define meta-dehumanization as the felt awareness of being seen as less than fully human by another party – bridging the gap between the AI's data-driven processing and the consumer's subjective response. Recent research further suggests that AI systems can themselves become perceived sources of dehumanization in consumer contexts (Chen et al., 2024). In personalized pricing, this may be particularly salient; when a price is determined by an algorithm, the consumer is implicitly informed that their worth was calculated from data rather than recognized by someone capable of appreciating individual circumstances. Because meta-dehumanization is rooted in the perception that the deciding entity lacks warmth and individual recognition (Kteily et al., 2016), and AI systems are perceived as calculative and rigid compared to humans (Lee, 2018; Chen et al., 2024), the source of the pricing decision may therefore serve as a critical cue. Therefore, we hypothesize that:

H2a: *Pricing source (AI vs human) affects perceived dehumanization, meaning that AI-generated pricing leads to higher perceived dehumanization than human-generated pricing.*

Further, Söderlund and Oikarinen (2021) demonstrated that consumers evaluate service encounters more positively when they perceive them as more human. Accordingly, as humanness and dehumanization represent opposing ends of the same continuum, interactions where consumers feel reduced rather than recognized as individuals may undermine satisfaction accordingly (Kteily et al., 2016; Waytz & Schroeder, 2014). Therefore, we hypothesize that:

H2b: *Perceived dehumanization negatively affects satisfaction with the pricing process.*

Finally, these consequences extend beyond the immediate transaction and are attributed to the retailer responsible for it. Kteily et al. (2016) showed that meta-dehumanization generates hostility toward the perceived perpetrator, i.e., the retailer. Furthermore, Chen et al., (2024) found that consumers who feel dehumanized through AI distance themselves from the organizations deploying those systems, because the retailer, not the algorithm, is understood as the accountable party. When a retailer's pricing communicates indifference to individual circumstance, it is therefore expected to erode goodwill and produce more negative attitudes toward the retailer as a brand. Therefore, we hypothesize that:

H2c: *Perceived dehumanization negatively affects attitude towards the retailer.*

2.5 Procedural Justice

Beyond how consumers feel about being treated as individuals, they also evaluate whether the process through which their price was determined was legitimate. Independent of whether the outcome is favorable or not, procedural justice refers to the perceived fairness of the decision-making process itself (Colquitt, 2001; Leventhal, 1980).

In personalized contexts, procedural considerations may become particularly salient. Haws and Bearden (2006) demonstrated that consumer-based price differentiation (i.e., where the same product is offered at different prices to different customers) generates especially strong fairness concerns relative to other forms of dynamic pricing. Algorithmic pricing creates a specific challenge in this regard – as it not only treats consumers differently but simultaneously limits their ability to evaluate how their price compares to others. Additionally, when outcome information cannot be observed, consumers shift their evaluation to the process itself, relying more heavily on procedural cues to determine whether they were treated fairly (Van den Bos et al., 2001; Van den Bos et al., 1997; Ferguson et al., 2014). The question consumers implicitly ask is therefore not only "is this price fair?" but rather "was the process that produced it fair?"

On one hand, algorithms are associated with objectivity, consistency, and reduced human bias, which can lead AI-generated decisions to be perceived as equally fair or even fairer than human ones (Araujo, 2020; Duani et al., 2024; Lee & Sharma, 2025). On the other hand, the "black box" nature of algorithmic systems means that consumers may have no effective way to observe how their price was calculated or challenge an unfavorable outcome (Gasser & Almeida, 2017). Unlike a human employee who can be questioned or held accountable, algorithmic pricing systems offer no accessible channel for explanation or contestation (Decker et al., 2025; Fang et al., 2025). In algorithmic pricing contexts, this opacity is further compounded by the individually tailored nature of the price, referring to the fact that consumers cannot compare their outcome to others, leaving the process itself as the primary basis for evaluation. Consumers are therefore asked to accept an individually calculated price without meaningful insight into how it was determined. Therefore, we hypothesize that:

H3a: *Pricing source disclosure (AI vs. human) affects perceived procedural justice, meaning that AI-generated pricing leads to lower perceived procedural justice than human-generated pricing.*

Further, when consumers perceive the pricing procedure as fair, they are more likely to respond positively to the transaction overall, even when the price is not numerically advantageous (Haws & Bearden, 2006; Ferguson et al., 2014). Therefore, we hypothesize that:

H3b: *Perceived procedural justice positively affects satisfaction with the pricing process.*

Beyond the immediate transaction, procedural information also signals what consumers can expect from the retailer in the future (Van den Bos et al., 1997). A process experienced as opaque and unaccountable therefore erodes not just satisfaction with the transaction, but broader attitudes toward the responsible retailer (Xia et al., 2004). Therefore, we hypothesize that:

H3c: *Perceived procedural justice positively affects attitude towards the retailer.*

2.6 Ulterior Motives

A primary driver of AI-driven personalized pricing is profit maximization, not merely through matching supply with demand, but by identifying and extracting each individual customer's willingness to pay (Bar-Gill, 2019). How consumers interpret the intentions behind such pricing therefore matters; prior research shows that consumers respond more negatively when they believe a retailer is acting out of self-serving or exploitative intentions rather than legitimate marketplace reasons (Campbell, 1999; Bolton et al., 2003; Xia et al., 2004).

This concern may be particularly salient in algorithmic pricing contexts, where opacity limits consumers' ability to understand how their price was determined or whose interests it ultimately serves (Van der Rest et al., 2020; Deng et al., 2022). Suspicion need not require objective proof of a worse deal – it may arise simply because the procedure appears strategically personalized yet impossible to interpret (Campbell, 1999; Deng et al., 2022). This is compounded by the fact that even advantageous personalized prices can trigger unfairness perceptions when they violate norms of equal treatment (Ohlwein & Bruno, 2025), and that algorithmic pricing intensifies information asymmetries in ways consumers may perceive as exploitative (Wagner & Eidenmüller, 2019; Chen et al., 2024).

While algorithms are sometimes perceived as more neutral than humans – lacking autonomous greed (Hwang et al., 2025; Usman et al., 2024) – this neutrality breaks down when firm interests are salient, redirecting suspicion toward the retailer itself (Campbell, 1999; Deng et al., 2022). Because AI-driven pricing is oriented toward revenue maximization and individual surplus extraction rather than interpersonal judgment (Bar-Gill, 2019; Wagner & Eidenmüller, 2019), it may offer consumers little interpretive space for a benevolent account. Therefore, we hypothesize that:

H4a: *Pricing source (AI vs human) affects perceived ulterior motives, such that AI-generated pricing leads to stronger perceptions of ulterior motives than human-generated pricing.*

When consumers believe a retailer is strategically optimizing prices in its own favor, suspicion of the seller's motives undermines the perceived legitimacy of the pricing process, regardless of whether the final price is objectively advantageous (Ohlwein & Bruno, 2025; Campbell, 1999). Therefore, we hypothesize that:

H4b: *Perceived ulterior motives negatively affect satisfaction with the pricing process.*

These consequences may also extend to the retailer itself. Although consumers may sometimes judge algorithms less harshly because they are perceived as lacking intentionality or autonomous greed (Duani et al., 2024; Gray & Wegner, 2009; Bigman et al., 2019), this does not necessarily absolve the retailer. In personalized pricing contexts, consumers are likely to attribute intent to the firm that chose to implement the system and benefits from its outcomes. Pricing practices perceived as exploitative or self-serving may therefore erode goodwill and produce more negative attitudes toward the retailer overall. Therefore, we hypothesize that:

H4c: *Perceived ulterior motives negatively affect attitude towards the retailer.*

2.7 Subjective Socioeconomic Status (Subjective SES)

Subjective socioeconomic status refers to individuals' perceived position within the social hierarchy relative to others, typically based on factors such as income, education, and occupational status (Adler et al., 2000). Unlike objective SES measures, subjective SES captures the psychological experience of social rank and relative disadvantage (Kraus et al., 2012).

Recent research on AI-driven decision contexts increasingly suggests that consumer responses to such experiences are not necessarily uniform, but rather influenced by individuals' backgrounds, experiences, and perceived social positions (Puntoni et al., 2021; Xie et al., 2024). Subjective SES may therefore function as a boundary condition moderating the psychological impact of AI-driven pricing, such that its effects on perceived dehumanization, procedural justice, and ulterior motives may be more pronounced among lower-SES consumers – though the direction and magnitude of these effects may vary across mediators.

2.7.1 Dehumanization x SES

Gray and Wegner (2012) suggest that machines become unnerving when they possess agency (the power to act) but lack experience and the capacity to feel. We argue that this experience gap may be particularly salient for lower-SES consumers, who are likely to experience meta-dehumanization – the acute awareness that society views them as "lesser" or as mere objects (Kteily et al., 2016; Sainz et al., 2021). Operating within what Sainz et al. (2026) describe as a "dehumanizing normative climate," lower-SES consumers may therefore find that being priced by an algorithm may act as a further dehumanizing trigger, reinforcing perceptions of being treated as a data point rather than as a unique individual. Therefore, we hypothesize that:

H5a: *Socioeconomic status moderates the relationship between pricing source and perceived dehumanization, meaning that the effect of AI-generated pricing on perceived dehumanization is stronger among lower-SES* customers.

2.7.2 Procedural Justice x SES

Fairness itself is a "socially shaped" construct – meaning that perceptions are not uniform but are systematically shaped by the characteristics of the evaluator (Nguyen et al., 2024; Starke et al., 2022). We argue that socioeconomic status is precisely such a characteristic, as lower-SES individuals apply stricter moral standards to others' behavior and are more sensitive to perceived injustices (Wang et al., 2021), in part because their environments are defined by persistent external constraints and institutional power asymmetries that chronically reduce their sense of personal control (Kraus et al., 2012). Because procedural justice hinges precisely on perceived control over the decision-making process (Leventhal, 1980), lower-SES consumers may therefore be more likely to evaluate opaque algorithmic pricing systems as procedurally unjust. Therefore, we hypothesize that:

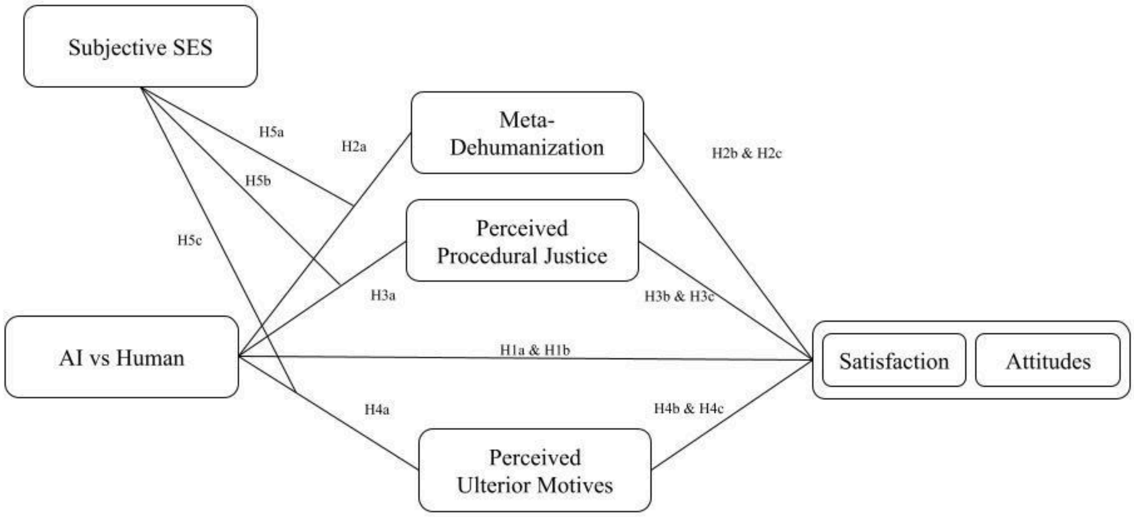
H5b. *Socioeconomic status moderates the relationship between pricing source and perceived procedural justice, such that the negative effect of AI-generated pricing on perceived procedural justice is stronger among lower-SES* customers.

2.7.3 Ulterior motives x SES

Lower-SES individuals tend to perceive outcomes as more strongly shaped by external social forces and situational constraints, leading them to become more attentive to contextual cues and potential power asymmetries (Kraus et al., 2011). Building on this, Kraus et al. (2012) further argue that social class shapes fundamental cognitive orientations: lower-SES individuals adopt a "contextualist" mindset, characterized by heightened sensitivity to external and uncontrollable social forces as well as a lower sense of personal control, whereas higher-SES individuals tend toward a more "solipsistic" orientation focused on internal goals and personal agency. In algorithmic pricing, where processes are opaque and difficult to contest, lower-SES consumers may therefore be more likely to infer that retailers are acting opportunistically or prioritizing profit maximization at the consumer's expense. Therefore, we hypothesize that:

H5c: *Socioeconomic status moderates the relationship between pricing source and perceived ulterior motives, such that the effect of AI-generated pricing on perceived ulterior motives is stronger among lower-SES* customers.

3. Conceptual Model



4. Methodology

4.1 Research Design

This study applied a quantitative scenario-based experimental design to examine how disclosure of pricing source, specifically artificial intelligence (AI) *versus* human staff, influences consumer responses to personalized pricing. Participants were randomly assigned to one of two experimental conditions in which an identical personalized offer was presented, differing only in attribution source. Consistent with experimental design principles, all elements of the scenario were kept constant except for the independent variable of interest (pricing source) to isolate its effect on evaluations (Söderlund, 2018).

This design was selected for several reasons. First, a random assignment strengthens causal inference by mitigating alternative explanations (Colquitt, 2008; Antonakis, 2017). Second, the single-factor design mirrors recent studies on algorithmic versus human-led price discrimination, which similarly isolate agent type as the focal experimental manipulation to reveal underlying psychological mechanisms (Duani et al., 2024; Li et al., 2025). Third, controlled experiments are appropriate when the objective is to identify causal relationships, provided that treatments remain theoretically relevant and free from confounding influences (Lonati et al., 2018).

The scenario was designed to resemble a realistic online retail environment, consistent with established practices in consumer research that emphasize how realistic stimuli help enhance ecological validity while maintaining experimental control (Geuens & De Pelsmacker, 2017). While such realism may strengthen external validity and support broader relevance of the findings (Colquitt, 2008), the design remains centered on validly isolating the theoretical mechanism rather than merely mimicking reality (Highhouse, 2009).

A significance level of .05 was adopted following standard research practice (Söderlund, 2018).

4.2 Manipulation

After GDPR and consent information, participants were presented with a scenario in which they were asked to imagine shopping online for a pair of white sneakers from a well-known retailer. They were informed that, based on information previously shared with the retailer, a personalized price had been determined specifically for them, meaning that the displayed price could differ from prices shown to other consumers (See appendix 1 and appendix 2).

The product page displayed a personalized offer of 799 SEK. To manipulate the pricing source, participants were randomly assigned to one of two experimental conditions. In the AI condition, participants were informed that the personalized price had been generated automatically through an AI-based pricing system using information shared on the website together with available consumers and market information. In the human condition, they were informed that the same information had instead been reviewed and used by company staff to determine the personalized price. The wording and visual presentation were kept identical across conditions, with pricing source being the only element that varied between the experimental groups.

To verify that participants recognized the intended manipulation, a factual manipulation check asked who they believed had been responsible for determining the price (AI/computer program; human staff member; or not sure). This was deliberately kept factual and non-evaluative, as Hauser et al. (2018) caution that manipulation checks may themselves influence participants' responses if they introduce additional interpretation or draw attention to the study purpose. An instructional attention check was also included to identify inattentive responses (Söderlund, 2018), where participants were instructed to select the value 5 when rating a statement, allowing inattentive responses to be identified without interfering with the substantive measures.

4.3 Measures

All constructs were measured using previously validated scales adapted to fit the pricing context of the study. Unless otherwise stated, items were measured using seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree). All multi-item measures were assessed for reliability using Cronbach's alpha (α). A cut-off value of $\alpha \geq .70$ was used to indicate acceptable internal consistency, in line with common reliability guidelines (Tavakol & Dennick, 2011).

Perceived dehumanization was measured using an adapted short-form version of the scale validated by Lagios et al. (2024), based on the original organizational dehumanization scale developed by Caesens et al. (2017). The items assessed whether participants felt treated impersonally or objectified by the retailer in relation to the pricing process (e.g "I feel that the retailer treated me as if I were an instrument or tool." and "I feel that the retailer treated me as if I were a number rather than a person."). The measurement scored a Cronbach's alpha of $\alpha = .872$.

Procedural justice was measured using an adapted version of the procedural justice scale developed by Colquitt (2001). The original scale captures perceived fairness of decision-making procedures across dimensions such as consistency, bias suppression, accuracy, correctability, and ethicality. In the present study, items were adapted to reflect how participants evaluated the procedure through which the personalized price had been determined. The measurement scored a Cronbach's alpha of $\alpha = 0.765$.

Perceived ulterior motives were measured using items adapted from Deng et al. (2022), originally developed to assess perceived manipulative intent in promotional settings. The adapted items captured the extent to which participants believed that the retailer's pricing decision was primarily driven by self-serving motives. The measurement scored a Cronbach's alpha of $\alpha = .818$.

Satisfaction with the pricing process was measured using three items adapted from Söderlund & Rosengren (2008), based on established customer satisfaction measures originally developed by Fornell (1992). The items captured overall satisfaction, expectation fulfillment, and perceived closeness to an ideal pricing process. The measurement scored a Cronbach's alpha of α = 0.875

Attitudes toward the retailer were measured using semantic differential items adapted from MacKenzie & Lutz (1989), where participants evaluated each object using bipolar adjective pairs such as bad/good, unfavorable/favorable, and dislike/like. The measurement scored a Cronbach's alpha of α = 0.919

Subjective socioeconomic status was measured using the Adler et al. (2000) MacArthur Scale of Subjective Social Status. Participants were shown a ten-rung ladder representing social standing in Sweden and asked to indicate where they perceived themselves relative to others in terms of income, education, and occupational status "Think of a ladder with 10 steps representing where people stand in Sweden. At step 10 are people with the highest levels of income, education, and occupational status. At step 1 are people with the lowest levels of income, education, and occupational status or unemployment. Where would you place yourself on this ladder?"

4.4 Use of AI tools

AI-based tools were used during the process as supportive aids for language editing, structural refinement, and clarification of argumentation. In addition, AI tools were used to assist in formulating and communicating statistical interpretation in written form, including non-significant findings and exploratory analyses. The tools were not used to conduct the statistical analyses themselves. All analyses, decisions regarding model specification, evaluation of results, and final interpretations were carried out and critically assessed by the authors. Any AI-generated suggestions were reviewed, revised, and checked against the empirical output before being incorporated.

4.5 Sample Characteristics

Participants were recruited through two channels: the authors' professional network and Prolific. Participants recruited from Prolific needed to live in Sweden and speak English fluently. This enabled random assignment across conditions and access to adult respondents meeting the predefined inclusion criteria.

Because the proposed model includes parallel mediators and a moderator, statistical power requirements exceed those of simple mediation models. Fritz and MacKinnon (2007) suggest that detecting indirect effects with small-to-medium path sizes often requires sample sizes above 400 observations in simpler mediation settings. However, given practical and financial constraints, the present study collected a total of 326 responses. This shortfall should be considered when interpreting the findings, particularly regarding the detection of subtle indirect effects

A post hoc sensitivity analysis was conducted to assess whether the achieved sample size provided sufficient statistical power to detect effects of practical relevance (Fritz and MacKinnon, 2007). Using G*Power with an alpha level of .05, a power of .80, and four predictors (AI/Human, Procedural justice, Dehumanization, Ulterior Motives), the achieved sample size of 289 corresponded to a minimum detectable effect size of $f^2 = .042$, indicating sensitivity to detect effects between small and medium magnitude. For the second analysis, the corresponding minimum detectable effect size was $f^2 = .052$, likewise suggesting sufficient power to detect approximately small-to-medium effects.

To ensure robustness, participants who failed the factual manipulation check were removed to ensure that only respondents who correctly recognized the pricing source were retained in the final dataset. This resulted in a final analytical sample of **237** respondents (54.0% male, 45.1% female, and 0.8% non-binary; age distribution: 21.5% aged 18–24, 27.8% aged 25–34, 22.8% aged 35–44, 14.8% aged 45–54, 12.2% aged 55–64, and 0.8% aged 65 years or older), constituting an 18% reduction from the initial post-attention-check sample of 289. This exclusion strengthens internal validity by ensuring that the main analyses are based on respondents who recognized the intended pricing-source manipulation.

Of the respondents, **130** correctly confirmed the AI condition (51.5% male, 48.5% female; age distribution: 22.3% aged 18–24, 24.6% aged 25–34, 18.5% aged 35–44, 19.2% aged 45–54, 13.8% aged 55–64, and 1.5% aged 65 years or older) and **107** the human condition (57.0% male, 41.1% female, and 1.9% non-binary; age distribution: 20.6% aged 18–24, 31.8% aged 25–34, 28.0% aged 35–44, 9.3% aged 45–54, and 10.3% aged 55–64).

Independent samples t-test confirmed no significant age differences between the groups ($t(235) = 1.46$, $p = .146$). In addition, a Pearson chi-square test showed no significant difference in gender distribution across conditions ($\chi^2(2) = 3.456$, $p = .178$), indicating that random assignment produced demographically comparable groups.

5. Results

5.1 T-test – Direct Effects of Pricing Source

To examine whether pricing source disclosure influences customer responses, an independent t-test was conducted. We report results based on the respondents who passed the manipulation check (n = 237). No significant difference was observed between conditions (AI or Human) for satisfaction ($t(235) = 0.23$, $p = .819$) nor attitudes toward the retailer ($t(235) = 0.48$, $p = .630$). Effect sizes were negligible for both satisfaction (Cohen's $d = .030$) and attitude (Cohen's $d = .063$). Accordingly, **H1a and H1b were not supported.**

Table 1. Direct effects of pricing source on satisfaction and attitude toward the retailer

Outcome variable	t(df)	p-value	Cohen's d	Result
Satisfaction	0.23 (235)	.819	.030	*Not significant*
Attitude toward the retailer	0.48 (235)	.630	.063	*Not significant*

The direction and significance of the results do not change if we include participants who failed the manipulation check.

5.2 Mediation Analysis

Satisfaction

Mediation analysis was conducted using Hayes' (2022) PROCESS macro (Model 4; 5,000 bootstrap samples), with the AI/Human condition as the independent variable (AI = 1, Human = 2). Each mediator was tested separately for satisfaction and attitude toward the retailer.

No significant difference was observed between conditions for **dehumanization** ($b = 0.01$, $se = 0.17$, $t(235) = 0.07$, $p = .942$), and no significant difference was observed for satisfaction directly ($b = -0.03$, $se = 0.14$, $t(234) = -0.23$, $p = .821$). Higher dehumanization was, however, significantly associated with lower satisfaction ($b = -0.58$, $se = 0.05$, $t(234) = -10.51$, $p < .001$), **supporting H2b.** The overall outcome model was significant ($R^2 = .32$, $F(2, 234) = 55.23$, $p < .001$). No significant indirect effect was observed through dehumanization (*Effect* = −0.007, *BootSE* = 0.100, 95% CI [−0.206, 0.186]), indicating that dehumanization did not mediate the relationship between agent type and satisfaction.

No significant difference was observed between conditions for **procedural justice** (b = 0.002, se = 0.13, $t(235) = 0.01$, p = .988), nor for satisfaction directly (b = −0.04, se = 0.14, $t(234) = −0.29$, p = .775). Higher procedural justice was, however, significantly associated with higher satisfaction (b = 0.75, se = 0.07, $t(234) = 10.45$, $p < .001$), **supporting H3b**. The overall outcome model was significant ($R^2 = .32$, $F(2, 234) = 54.68$, $p < .001$). No significant indirect effect was observed through procedural justice (*Effect* = 0.001, *BootSE* = 0.101, 95% CI [−0.199, 0.198]), indicating that procedural justice did not mediate the relationship between agent type and satisfaction.

No significant difference was observed between conditions for **ulterior motives** (b = 0.09, se = 0.14, $t(235) = 0.66$, p = .512), nor for satisfaction directly (b = 0.03, se = 0.14, $t(234)$ = 0.19, p = .853). Stronger perceptions of ulterior motives were, however, significantly associated with lower satisfaction (b = −0.71, se = 0.07, $t(234) = −10.85$, $p < .001$), **supporting H4b**. The overall outcome model was significant ($R^2 = .33$, $F(2, 234) = 58.91$, $p < .001$). No significant indirect effect was observed through ulterior motives (*Effect* = −0.066, *BootSE* = 0.100, 95% CI [−0.264, 0.130]), indicating that ulterior motives did not mediate the relationship between agent type and satisfaction.

Table 2. Mediation results for satisfaction

Mediator	**a-path**	**b-path**	**c'-path**	**Indirect effect**	**95% CI**	**Result**
Dehumanization	0.01	-0.58***	-0.03	-0.007	[-0.206, 0.186]	*No mediation*
Procedural justice	0.002	0.75***	-0.04	0.001	[-0.199, 0.198]	*No mediation*
Ulterior motives	0.09	-0.71***	0.03	-0.066	[-0.264, 0.130]	*No mediation*

The a-path refers to the effect of pricing source on the mediator. The b-path refers to the effect of the mediator on satisfaction. The c′-path refers to the direct effect of pricing source on satisfaction when the mediator is included.

The direction and significance of the results do not change if we include participants who failed the manipulation check.

Attitude toward the retailer

No significant difference was observed between conditions for **dehumanization** (b = 0.001, se = 0.17, t(236) = 0.01, p = .996), nor for attitude directly (b = −0.07, se = 0.14, t(235) = −0.52, p = .606). Higher dehumanization was significantly associated with more negative attitudes toward the retailer (b = −0.60, se = 0.05, t(235) = −11.26, p < .001), **supporting H2c**. The overall outcome model was significant (R^2 = .35, F(2, 235) = 63.53, p < .001). No significant indirect effect was observed through dehumanization (*Effect* = −0.001, *BootSE* = 0.103, 95% CI [−0.206, 0.198]), indicating that dehumanization did not mediate the relationship between agent type and attitude toward the retailer.

No significant difference was observed between conditions for **procedural justice** (b = 0.02, se = 0.13, t(236) = 0.18, p = .858), nor for attitude directly (b = −0.09, se = 0.14, t(235) = −0.64, p = .521). Higher procedural justice was significantly associated with more positive attitudes toward the retailer (b = 0.76, se = 0.07, t(235) = 10.91, p < .001), **supporting H3c**. The overall outcome model was significant (R^2 = .34, F(2, 235) = 59.69, p < .001). No significant indirect effect was observed through procedural justice (*Effect* = 0.018, *BootSE* = 0.103, 95% CI [−0.184, 0.222]), indicating that procedural justice did not mediate the relationship between agent type and attitude toward the retailer.

No significant difference was observed between conditions for **ulterior motives** (b = 0.08, se = 0.14, t(236) = 0.57, p = .567), nor for attitude directly (b = −0.005, se = 0.13, t(235) = −0.04, p = .968). Stronger perceptions of ulterior motives were significantly associated with more negative attitudes toward the retailer (b = −0.84, se = 0.06, t(235) = −14.31, p < .001), **supporting H4c**. The overall outcome model was significant (R^2 = .47, F(2, 235) = 102.61, p < .001). No significant indirect effect was observed through ulterior motives (*Effect* = −0.068, *BootSE* = 0.119, 95% CI [−0.312, 0.160]), indicating that ulterior motives did not mediate the relationship between agent type and attitude toward the retailer.

Table 3. Mediation results for attitude toward the retailer

Mediator	**a-path**	**b-path**	**c'-path**	**Indirect effect**	**95% CI**	**Result**
Dehumanization	0.001	−0.60***	−0.07	−0.001	[-0.206, 0.198]	*No mediation*
Procedural justice	0.02	0.76***	−0.09	0.018	[-0.184, 0.222]	*No mediation*
Ulterior motives	0.08	−0.84***	−0.005	−0.068	[-0.312, 0.160]	*No mediation*

The a-path refers to the effect of pricing source on the mediator. The b-path refers to the effect of the mediator on attitude toward the retailer. The c′-path refers to the direct effect of pricing source on attitude toward the retailer when the mediator is included.

The direction and significance of the results do not change if we include participants who failed the manipulation check.

5.3 Moderated mediation

5.3.1 Main analysis

To examine whether subjective socioeconomic status (SES) moderated the indirect effects of agent type on satisfaction and attitude toward the retailer, a moderated mediation analysis was conducted using Hayes' (2022) PROCESS macro (Model 7; 5,000 bootstrap samples). SES was first treated as a continuous moderator (ranging from 1–10), with dehumanization, procedural justice, and ulterior motives as simultaneous mediators.

Satisfaction

The outcome model was significant ($R^2 = .49$, $F(4, 232) = 55.70$, $p < .001$). All three mediators were significantly associated with satisfaction: dehumanization ($b = -0.27$, $p < .001$), procedural justice ($b = 0.43$, $p < .001$), and ulterior motives ($b = -0.34$, $p < .001$). No significant direct effect of agent type on satisfaction was observed ($b = -0.006$, $p = .961$). No significant first-stage interactions between agent type and SES were observed across the three mediator models (all *p*s > .12), and all indices of moderated mediation included zero within their 95% bootstrap confidence intervals. Accordingly, **H5a, H5b, and H5c were not supported for satisfaction**.

Attitude toward the retailer

A similar pattern was observed for attitude toward the retailer. The outcome model was significant (R^2 = .58, $F(4, 233) = 81.12$, $p < .001$). All three mediators were significantly associated with attitude: dehumanization ($b = -0.22$, $p < .001$), procedural justice ($b = 0.38$, $p < .001$), and ulterior motives ($b = -0.51$, $p < .001$). No significant direct effect of agent type on attitude was observed ($b = -0.04$, $p = .723$). No significant first-stage interactions between agent type and SES were observed across the three mediator models (all ps > .14), and all indices of moderated mediation included zero within their 95% bootstrap confidence intervals. Accordingly, **H5a, H5b, and H5c were not supported for attitude toward the retailer**.

Table 4. Moderated mediation results with SES as a continuous moderator

Outcome	**R²**	**Direct effect**	**Dehumanization**	**Procedural justice**	**Ulterior motives**	**Interaction terms**	**Result**
Satisfaction	.49	-0.006	-0.27***	0.43***	-0.34***	n.s	*Not supported*
Attitude toward the retailer	.58	-0.04	-0.22***	0.38***	-0.51***	n.s	*Not supported*

The direction and significance of these results do not change if we include participants who failed the manipulation check.

5.3.2 Exploratory analysis

Inspection of the SES distribution revealed a right skew, with a concentration of responses in the higher range of the scale ($M = 5.97$, $SD = 1.76$; see Appendix 3 for histogram), suggesting that the sample was predominantly composed of higher SES individuals. This may have limited the ability to detect moderation effects in the continuous analysis. To explore whether results differed across SES levels, participants were divided into two groups based on a mean split: low SES (scores 1–5) and high SES (scores 6–10), and the moderated mediation analyses were rerun.

Satisfaction

When SES was operationalized as a binary moderator, a different pattern emerged for the dehumanization pathway. A significant interaction between agent type and SES group was observed for dehumanization (b = 0.76, se = 0.35, $t(232)$ = 2.16, p = .032, ΔR^2 = .020), indicating that the relationship between agent type and dehumanization differed across SES groups. Among low-SES individuals, a negative association between agent type and dehumanization was observed (b = −0.45, p = .110), while among high-SES individuals a positive association was observed (b = 0.31, p = .148), though neither conditional effect reached significance individually.

The index of moderated mediation through dehumanization was significant (*Index* = −0.21, *BootSE* = 0.118, 95% CI [−0.472, −0.013]), indicating that SES significantly moderated the indirect effect of agent type on satisfaction through dehumanization, providing **partial exploratory support for H5a**. No significant indirect effects were observed through ulterior motives or procedural justice across both SES groups (all 95% CIs included zero). No significant direct effect of agent type on satisfaction was observed (b = −0.004, p = .973).

Attitude toward the retailer

A similar pattern was observed for attitude toward the retailer. A significant interaction between agent type and SES group was observed for dehumanization (b = 0.74, se = 0.35, $t(233)$ = 2.10, p = .037, ΔR^2 = .018), with a negative association observed among low-SES (b = −0.45, p = .110) and a positive association among high-SES individuals (b = 0.29, p = .177), though again neither conditional effect reached significance individually.

The index of moderated mediation through dehumanization was significant (*Index* = −0.16, *BootSE* = 0.101, 95% CI [−0.395, −0.004]), indicating that SES significantly moderated the indirect effect of agent type on attitude through dehumanization, again providing **partial exploratory support for H5a**. No significant indirect effects were observed through ulterior motives or procedural justice across both SES groups (all 95% CIs included zero). No significant direct effect of agent type on attitude was observed (b = −0.04, p = .704).

Table 5. Moderated mediation results of dehumanization with SES as a binary moderator

Outcome	**b**	**p**	**Low SES b**	**Low SES p**	**High SES b**	**High SES p**	**Index**	**95% CI**	**Result**
Satisfaction	0.76	.032	−0.45	.110	0.31	.148	−0.21	[−0.472, −0.013]	*Partially supported*
Attitude toward the retailer	0.74	.037	−0.45	.110	0.29	.177	−0.16	[−0.395, −0.004]	*Partially supported*

The direction and significance of these results do not change if we include participants who failed the manipulation check.

5.4 Summary of hypothesis testing

Hypothesis	Description	Result
H1a	AI-generated pricing leads to lower satisfaction than human-generated pricing	*Not supported*
H1b	AI-generated pricing leads to more negative attitudes toward the retailer than human-generated pricing	*Not supported*
H2a	AI-generated pricing leads to higher perceived dehumanization than human-generated pricing	*Not supported*
H2b	Perceived dehumanization negatively affects satisfaction	*Supported*
H2c	Perceived dehumanization negatively affects attitude toward the retailer	*Supported*
H3a	AI-generated pricing leads to lower perceived procedural justice than human-generated pricing	*Not supported*
H3b	Perceived procedural justice positively affects satisfaction	*Supported*
H3c	Perceived procedural justice positively affects attitude toward the retailer	*Supported*
H4a	AI-generated pricing leads to stronger perceptions of ulterior motives than human-generated pricing	*Not supported*
H4b	Perceived ulterior motives negatively affect satisfaction	*Supported*
H4c	Perceived ulterior motives negatively affect attitude toward the retailer	*Supported*
H5a	SES moderates the effect of pricing source on perceived dehumanization, stronger among lower-SES customers	*Partially supported**
H5b	SES moderates the effect of pricing source on perceived procedural justice, stronger among lower-SES customers	*Not supported*
H5c	SES moderates the effect of pricing source on perceived ulterior motives, stronger among lower-SES customers	*Not supported*

*Supported only when SES is operationalized as a binary (mean-split) moderator, not as a continuous variable.

6. Discussion

6.1 Discussion of Mediators

Contrary to the proposed hypotheses, the findings did not reveal significant differences between AI-driven and human-driven pricing on either satisfaction or attitudes toward the retailer. Similarly, AI disclosure was not significantly associated with perceived dehumanization, procedural justice, or ulterior motives. Accordingly, none of the proposed mediation effects were supported. Importantly, however, all three mediators were significantly associated with both satisfaction and attitudes toward the retailer in the expected directions. Higher levels of dehumanization and ulterior motives were associated with lower satisfaction and more negative retailer attitudes, while procedural justice was positively associated with both outcomes.

Taken together, these findings may suggest that while consumers are responsive to perceptions of fairness, human recognition, and firm intentions, the mere disclosure that a price was generated by AI rather than a human may not be sufficient to meaningfully activate such perceptions within the examined context. In other words, the underlying psychological mechanisms appear relevant to consumers evaluations of personalized pricing, yet pricing-source disclosure alone did not significantly activate them in the present context.

6.2 Discussion of SES Moderation Effect

Contrary to H5a–H5c, subjective socioeconomic status did not significantly moderate the indirect effects of pricing source on satisfaction or attitudes toward the retailer when SES was treated as a continuous variable. None of the interaction terms between agent type and SES were significantly associated with dehumanization, procedural justice, or ulterior motives, and all indices of moderated mediation included zero within their bootstrap confidence intervals. These findings suggest that the indirect effects of AI versus human pricing did not systematically vary across SES levels within the primary analysis.

When SES was operationalized as a binary variable through a mean split, a different pattern emerged for the dehumanization pathway. Specifically, a significant interaction between agent type and SES group were observed for dehumanization in both the satisfaction and attitude models, and the indices of moderated mediation through dehumanization were significant. This provided partial exploratory support for H5a, suggesting that subjective socioeconomic position may shape how consumers interpret AI-driven pricing in relation to feelings of dehumanization. However, given the methodological constraints associated with the variable dichotomization and absence of significant conditional effects within each group individually, these findings should be treated as hypothesis-generating rather than confirmatory.

6.3 General discussion

The primary aim of this paper is to explore whether disclosing AI-generated personalized pricing triggers more negative consumer responses than human-generated pricing, and whether these effects are shaped by consumers' subjective socioeconomic status. The results show that the answer is not as clear-cut as initially anticipated. Anchored in algorithm aversion literature (e.g., Dietvorst et al., 2015; Castelo, 2019; Mahmud, 2022), we argued that AI disclosure would activate perceptions of dehumanization, procedural injustice, and ulterior motives, which in turn would reduce consumer satisfaction and attitudes toward the retailer. Across both the mediation and moderated mediation analyses, the mediators themselves were consistently and significantly associated with both outcomes in the expected directions. However, contrary to our expectations, AI pricing disclosure did not significantly differ from human pricing disclosure on any of the proposed mediators or outcomes. Conclusively, the psychological mechanisms matter, but pricing-source disclosure alone was not sufficient to activate them in the present context. To explain the non-significant findings we offer two possible explanations.

First, it may be that AI-driven personalization has become sufficiently normalized in contemporary retail environments and throughout society (Maedche et al., 2019), that consumers no longer perceive algorithmic involvement as novel or threatening. As firms progressively integrate AI into recommendation systems, customer service, and personalization, consumers may have developed a generalized expectation of algorithmic involvement in retail interactions (Cao et al., 2021; Guha et al., 2021). Such familiarity and exposure has been shown to reduce uncertainty (Montoya et al., 2017) and increase trust in technological agents (Komiak & Benbasat, 2006), making it plausible that participants in the present study simply did not perceive AI-generated pricing as sufficiently distinct from human-generated pricing to produce differential reactions.

A second explanation concerns the specific retail context used in the study. Participants evaluated a personalized pricing scenario involving a familiar, and low stake product category offered at a modest price point. As discussed in our hypothesis development, prior research suggests that consumer responses toward AI systems vary depending on task type and contexts (Castelo et al., 2019; Lee, 2018; Logg, 2019), while aversion and fairness concerns may be particularly pronounced when outcomes are personally consequential or financially significant (Haws & Bearden, 2006). The present study may therefore have represented a comparatively weak activation context, where AI involvement alone was insufficient to meaningfully trigger concerns regarding dehumanization, unfairness, or exploitative intent.

This contextual argument is also consistent with more recent evidence complicating the traditionally negative view of algorithmic decision-making. Duani et al. (2024) found that consumers sometimes perceive algorithmic pricing as fairer than equivalent human-driven pricing, partly because algorithms were viewed as less judgmental and more objective. This suggests that in familiar, low-stakes retail contexts, AI disclosure may carry neutral or even favorable connotations rather than triggering aversion, potentially dampening any differential response to AI versus human pricing in the present sample.

6.4 Theoretical Contribution

The results of this paper contribute to several fields of research. Foremost, this study responds to calls for a deeper understanding of the contextual and psychological conditions under which consumers develop negative reactions toward AI-driven marketplace decisions (Puntoni et al., 2021; Ohlwein & Bruno, 2025). While algorithm aversion has been studied across a range of consumer and organizational contexts (Dietvorst et al., 2015; Jussupow, 2024), and personalized pricing has been examined through the lenses of ethical concerns and perceived fairness (Seele et al., 2021; Priester et al., 2020), limited attention has been paid to how pricing-source disclosure specifically activates the psychological mechanisms through which consumers evaluate personalized pricing and how attitudes spillover towards the retailer. Our study reveals that dehumanization, procedural justice, and ulterior motives are meaningful evaluative lenses through which consumers assess personalized pricing processes, but that there is much left to learn about the conditions under which pricing-source disclosure is sufficient to activate them.

Further, present findings suggest that disclosure alone may constitute a comparatively weak psychological cue when algorithmic systems are already normalized within everyday retail environments. This supports a more context-dependent understanding of algorithmic aversion and appreciation (Castelo et al., 2019; Lee, 2018; Logg et al., 2019), and extends existing literature by identifying the low-stakes retail context as a potential boundary condition.

Third, by introducing subjective socioeconomic status as a moderating condition, this paper responds to broader calls for a more nuanced understanding of the psychological and contextual conditions shaping consumer reactions to AI-driven marketplace decisions (Puntoni et al., 2021; Ohlwein & Bruno, 2025). While the primary moderation hypotheses were not supported, the exploratory findings suggest that socioeconomic background may still influence how consumers interpret potentially dehumanizing pricing processes. In doing so, the study contributes to emerging research showing that perceptions of fairness and algorithmic decision-making differ across socioeconomic groups rather than remaining uniform across consumers (e.g., Nguyen et al., 2024; Xie et al., 2024).

6.5 Managerial Implications

For managers, understanding how consumers respond to AI-driven pricing systems is becoming increasingly important (Guha et al., 2021). As retailers increasingly explore the use of artificial intelligence in personalization, customer management, and pricing-related decision processes (Cao et al., 2021; Libai et al., 2020), firms are simultaneously under pressure to improve efficiency, optimize profitability, and maintain customer trust.While this study set out to demonstrate that AI disclosure would trigger consumer backlash, our findings did not support such an effect in the given context. Yet the study still advances several important insights for practitioners navigating the implementation of algorithmic pricing.

First, the findings suggest that disclosing AI involvement in pricing may not automatically damage consumer evaluations in relatively familiar retail contexts. As algorithmic personalization becomes increasingly embedded in everyday retail, consumers may no longer perceive AI pricing as particularly unusual or threatening. For managers, this provides some reassurance: the implementation of AI-driven pricing systems need not generate the strong consumer backlash often implied in public discourse, at least in low-stakes purchase environments.

At the same time, the results make clear that perceptions of dehumanization, procedural justice, and ulterior motives remain strongly associated with both satisfaction and retailer attitudes. Even if AI disclosure did not significantly activate these concerns in the present study, consumers are clearly sensitive to pricing processes perceived as impersonal, opaque, or exploitative. This means the managerial challenge is not primarily whether to use AI in pricing, but how such systems are designed, communicated, and experienced. Providing understandable explanations for personalized prices, maintaining accessible channels for contestation, and limiting the appearance of excessive profit extraction may all help protect consumer evaluations regardless of whether a human or algorithm sets the price.

6.6 Limitations & Future research

This study is subjected to several limitations that should be considered when interpreting the findings. These limitations do not invalidate the contributions, but constrain conclusions that can be drawn and guide important directions of future research.

The first limitation concerns the experimental stimulus and its capacity to activate the proposed psychological mechanisms. Participants evaluated a personalized pricing scenario involving a pair of white sneakers priced at 799 SEK – a product deliberately chosen for its neutrality and familiarity. While this strengthened experimental control, the scenario represents a relatively low-stakes and low-involvement purchase in which the financial and social consequences of a potentially unfair price are limited. Prior research suggests that fairness concerns become most salient when outcomes are consequential or when individuals perceive themselves to be at a relative disadvantage (Ferguson et al., 2014; Haws & Bearden, 2006). Thus, the stimulus, combined with subtle disclosure manipulation, may therefore have been insufficient to meaningfully activate proposed mechanisms.

This interpretation is further supported by the substantial number of respondents who failed the manipulation check (27%), suggesting that the distinction between AI- and human-generated pricing was not sufficiently psychologically salient to all participants. As Colquitt (2008) notes, experiments require not just surface realism but psychological realism, and that participants must genuinely experience the intended construct for the manipulation to be effective. The relatively high failure rate therefore suggests that many participants may not have attended to, remembered, or otherwise processed the disclosed pricing source as a central aspect of the pricing encounter. At the same time, consumers in real retail environments may similarly pay limited attention to such disclosures. Consequently, the failure rate may not only represent a methodological limitation but also suggest that pricing-source information is unlikely to be highly influential unless consumers actively notice and process it. Therefore, future research identifying the specific contextual conditions necessary to activate these mechanisms should be high on the research agenda; specifically, researchers should test the model in higher-involvement contexts such as insurance, travel, or healthcare pricing, where the psychological stakes of being priced by an algorithm are more acutely felt.

Second, a substantive limitation concerns statistical power. 326 responses were initially collected, the attention check reduced the sample to n = 286, and later the manipulation check reduced the sample to n = 237. A sample size exceeding 400 observations would be more appropriate to detect indirect effects of small-to medium magnitude in parallel mediation (Fritz & MacKinnon, 2007). While the post-hoc sensitivity analysis indicated that the achieved sample could detect effects of approximately $f^2 = .042$, the independent-samples t-tests showed negligible mean differences between the AI and human conditions (Cohen's d values of .030 for satisfaction; .063 for attitude toward the retailer). These values suggest that any pricing-source effect on the primary outcomes was very small in the present context. Consequently, while the achieved sample size may have reduced sensitivity to detect subtle indirect effects, the findings also suggest that any pricing-source effects in the present context were likely limited in magnitude and difficult to detect reliably. The null findings should therefore not be interpreted as definitive evidence that pricing-source disclosure has no effect, but rather that such effects may be weak and context-dependent. Future research should therefore aim to recruit larger samples, ideally exceeding 400 observations (Fritz & MacKinnon, 2007), while embedding the manipulation in a higher-involvement context – as suggested above – where effect sizes are more likely to be of sufficient magnitude to detect the proposed indirect effects reliably.

Third, the distribution of subjective socioeconomic status (SES) within the sample limits the conclusions that can be drawn regarding SES moderation. The SES distribution was markedly right-skewed with a mean of 5.97 (SD = 1.76) on a 10-point MacArthur Ladder scale and 63.7% of participants scoring in the upper half of the scale, resulting in insufficient representation of lower-SES consumers. This is not merely an effect of sampling error – Sweden is characterised by relatively compressed income inequality compared to many other

OECD countries (OECD, 2024), meaning that the relative absence of subjective low-SES respondents may partly reflect the structural reality of Swedish society. Nevertheless, the consequence for the present study is the same: reduced statistical power to detect moderated mediation hypothesized under H5. Further, the exploratory dichotomization of SES using a mean split, while yielding tentative support for H5a, is known to reduce statistical power and obscure variance (MacCallum et al., 2002), and should be treated as hypothesis-generating rather than confirmatory. Future research should therefore recruit more socioeconomically diverse samples, specifically oversampling lower-SES consumers, and consider replicating the study in countries (or regions) with greater socioeconomic stratification/diversification to provide a more robust test of the moderation hypotheses.

Finally, several measurement scales were adapted from prior literature to fit the context of AI-driven personalized pricing. While this approach is common, many of the validated scales were originally developed for other domains rather than personalized pricing specifically. It is therefore possible that some items were interpreted inconsistently by respondents or did not fully capture the intended constructs, introducing measurement error and potentially attenuating observed relationships. Future research should therefore address this by either developing and validating pricing-specific scales for the proposed mediators, or apply the model to already suitable ones for other psychological mechanisms, which could strengthen construct validity in this emerging research context.

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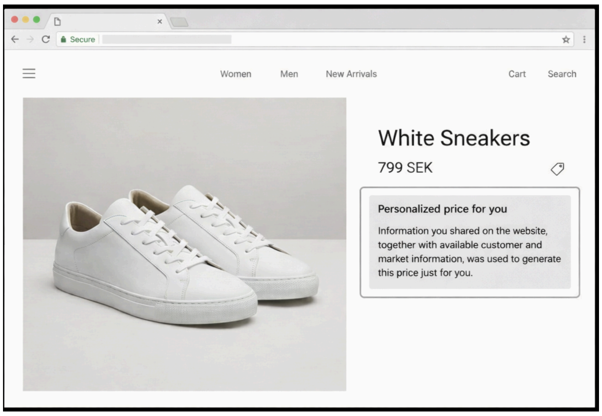
8. Appendix

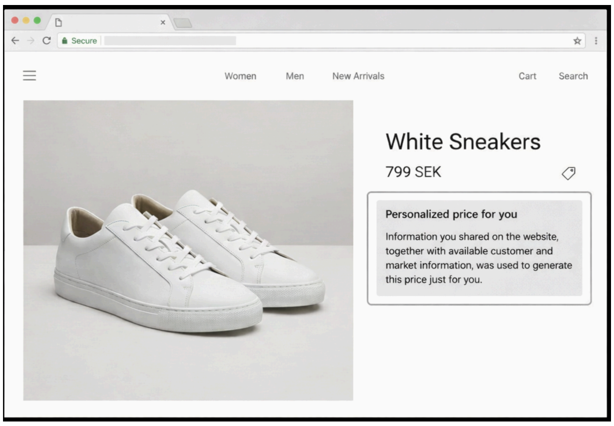
Appendix 1:

“Now, imagine that you are shopping online for a pair of sneakers from a well-known retailer. Based on personal information you have previously provided, the retailer calculates a personalized price specifically for you. This means the price you see may differ from the price shown to other customers. *This price was determined by **human staff** “

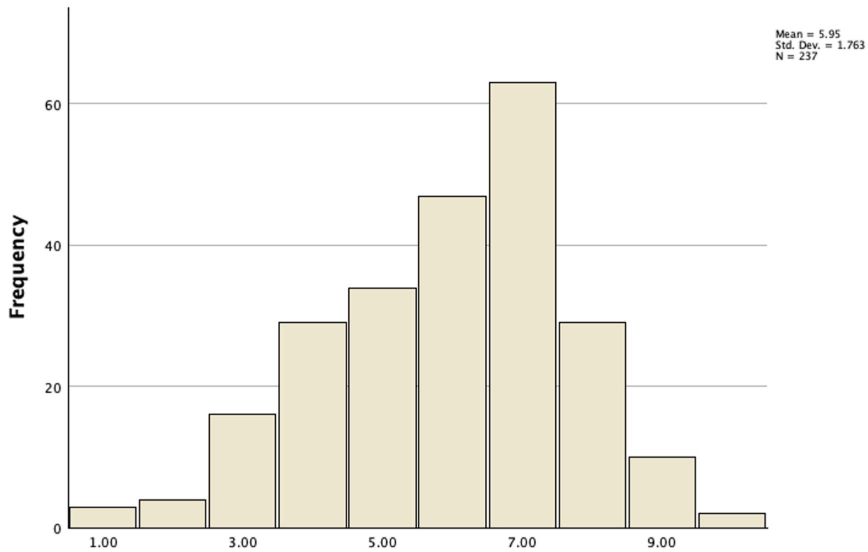


Appendix 2:

“Now, imagine that you are shopping online for a pair of sneakers from a well-known retailer. Based on personal information you have previously provided, the retailer calculates a personalized price specifically for you. This means the price you see may differ from the price shown to other customers. *This price was generated automatically through an **AI system**”



Appendix 3:



Mean = 5.95
Std. Dev. = 1.763
N = 237
Frequency
60
40
20
0
1.00
3.00
5.00
7.00
9.00

AI disclosure

The generative AI tools ChatGPT, Gemini, and Claude were used during this thesis process. ChatGPT was primarily used to support selected parts of both the research process (including clarifying errors, statistical results and numbers that we initially found difficult to interpret) and writing process (mainly refining and structuring language appropriately). For example, we asked ChatGPT to rewrite sentences to make them clearer, more concise, and grammatically correct. A typical prompt we used was: “Without changing the meaning, can you rewrite this to make it clearer and grammatically correct?”. In addition, we experimented with using AI to help generate possible ways of structuring our report and organizing potential sections. However, throughout the process, we continuously refined and adjusted the preliminary structure ourselves. Google Gemini was mainly used for interpreting results from prior research, for example, summarizing articles to gain a quicker initial understanding before reading more closely ourselves. Claude was used as an additional supportive tool, primarily for writing-related assistance, such as in terms of language refinement and structuring improvements, when working on tying different parts of the thesis together.

The use of these tools supported and streamlined our process in several ways. They helped us to work more efficiently with time-consuming tasks (such as finding grammatical errors), improving sentence structure, and finding clearer or more concise ways of formulating ourselves. This allowed us to spend more time on relevant papers, as well as for analyzing, interpreting, and discussing the results. However, the use of AI tools also involves some risks. In some cases, the AI-generated suggestions did not fully reflect what we intended in the prompts and risked changing the core meaning. To minimize this risk, we carefully and manually reviewed the outputs and tried to formulate specific and relevant prompts. In addition, AI tools may also generate misleading, or even inaccurate, information. We addressed this by ensuring that these tools were not used as sources of factual information or theoretical claims. (All academic content has been verified through peer-reviewed literature).

Overall, the use of generative AI supported our process, while also helping us develop a deeper understanding of how to formulate prompts, evaluate outputs critically, and how to use AI tools effectively, yet responsibly, in an academic context.