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AI-Powered Personalized Pricing Strategies

An Analysis of their Influence on Consumer Purchase Intentions

Diogo José Abreu da Silva

Master Thesis

presented as partial requirement for obtaining the Master Degree in Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa

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by

Diogo José Abreu da Silva

Master Thesis presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Information Systems and Technologies Management.

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, 13th July, 2024

ABSTRACT

This study investigates the influence of AI-powered personalized pricing strategies on consumer behavior in e-commerce, emphasizing trust and perceived fairness as pivotal factors. Through online experiments, the research reveals that consumers exhibit higher trust and fairness perceptions towards traditional pricing methods perceived as transparent and human-controlled, compared to AI-powered algorithms. The study identifies significant consumer skepticism towards AI-driven pricing, influencing preferences for human-established pricing. Mediation analyses underscore the critical roles of trust and perceived fairness in shaping consumer purchase intentions under different pricing scenarios. The findings contribute to a deeper understanding of AI pricing strategies in e-commerce, highlighting implications for trust-building strategies and fairness considerations in algorithmic pricing decisions.

KEYWORDS

AI-Powered Pricing; Consumer Behavior; Purchase Intention; Trust; Fairness

Sustainable Development Goals (SDG):



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LIST OF ABBREVIATIONS AND ACRONYMS

AI Artificial Intelligence

1. INTRODUCTION

As stated by Asker et al. (2023), in today's dynamic and competitive landscape, pricing strategies are pivotal in determining the success and profitability of companies and the emergence of Artificial Intelligence (AI) has inaugurated a fresh era in pricing tactics, providing businesses with powerful tools to optimize their pricing decisions. According to Bharadiya (2023), companies are progressively leaning on advanced algorithms, empowered by extensive repositories of customer preference data, to inform and shape their business intelligence capabilities. These algorithms utilize a learning process to develop strategies for engaging in pricing competition alongside other companies. These strategies have the potential to revolutionize how companies approach pricing, making it more responsive, personalized, and efficient. Nevertheless, as mentioned by Turow (2006), it is worth noting that the extent of consumer awareness concerning discriminatory pricing strategies has given rise to a culture characterized by skepticism and resentment, thus accentuating a growing societal concern.

As explained by Wang et al. (2022), automated pricing strategies in e-commerce can be broadly categorized into two forms - simple rule-based such as undercutting the lowest price, and more sophisticated artificial intelligence (AI) powered algorithms, such as reinforcement learning (RL) algorithms. Although simple rule-based pricing remains the most widely used strategy, a few retailers have adopted pricing algorithms powered by AI. RL algorithms are particularly appealing for pricing due to their abilities to autonomously learn an optimal policy and adapt to changes in competitors' pricing strategies and market environment.

While previous research made by Haws & Bearden (2006) and Alderighi et al. (2022) have touched upon the concept of dynamic pricing and the consumer perception on it, this study aims to explore the extent to which AI-powered personalized pricing strategies influence consumer purchase intentions, while also investigating how factors such as trust, privacy concerns and fairness perceptions influence the relationship between AI-powered personalized pricing and purchase intentions. Specifically, it investigates the main research question: To what extent do AI-powered personalized pricing strategies influence consumer purchase intentions, and what is the role of trust, privacy concerns, perceived fairness and price sensitivity in this relationship?

According to KPMG (2023), CEOs have identified generative AI as a top priority for their organizations, indicating a strong interest in harnessing the potential of AI for various business applications. This growing investment trend in new technology is indicative of a shift towards innovation and optimizing operations. AI's impact on profitability, market growth, innovation, and cybersecurity is evident, but it also raises ethical and regulatory concerns. This underscores the need for a well-informed approach to AI-powered strategies, aligning with ethical values and ensuring adherence to evolving regulations. Understanding the influence

of AI-powered personalized pricing on consumer behavior becomes crucial as businesses seek to leverage AI's transformative potential while addressing these challenges.

Bergen et al.'s (2021) article highlights the increasing concerns surrounding AI-enabled supercharged price discrimination. This practice, driven by AI algorithms and behavioral science, enables companies to tailor prices, raising important societal issues. Key concerns include access to essential products, potential harm to vulnerable populations, and the manipulation of customers through pricing strategies. To address these concerns, companies are encouraged to explore creative pricing solutions that balance profit and societal wellbeing, considering compromises when necessary, and incorporate ethical deliberation into their pricing decisions. These actions can help companies maintain profitability while aligning their strategies with societal values and preserving their brand reputation.

The objectives of the present research are to analyze the impact of AI-driven personalized pricing on consumer purchase intentions, investigate the moderating effects of individual factors such as price sensitivity on the relationship between personalized pricing and purchase intentions and provide insights into the consumer's trust, fairness perception and privacy concerns surrounding AI-powered personalized pricing in e-commerce.

This research presents a substantial opportunity for theoretical contributions within the academic landscape, particularly in the fields of marketing, consumer behavior, and artificial intelligence. The purpose of this research is to refine established consumer behavior models to accommodate the intricate and individualized nature of personalized pricing, thereby yielding a more nuanced comprehension of consumer responses to price alterations. Furthermore, it seeks to extend existing theoretical frameworks concerning personalization in e-commerce, elucidating the psychological and behavioral facets associated with personalized pricing. This research also addresses the theoretical underpinnings of trust and privacy concerns within the context of AI-powered personalized pricing, allowing for a comprehensive examination of how these factors shape consumer purchase intentions.

LITERATURE REVIEW

1.1. AI PRICING

As outlined by Sammut-Bonnici and Channon (2015), a pricing strategy serves as a firm's approach to determining the charges for its products and services. The selection of a pricing strategy is contingent upon the overall corporate strategy, buyer expectations and behavior, competitor strategies, industry dynamics, and regulatory constraints.

E-commerce pricing strategies include rule-based approaches like undercutting and advanced AI algorithms such as reinforcement learning (RL). Though rule-based methods dominate, some retailers opt for RL algorithms, valued for autonomous learning and adaptability to market changes (Wang et al., 2022).

Turow (2017) suggests the importance of ethical considerations as retailers employ algorithms as a mean of social discrimination. This involves sending customers distinct messages, and potentially different prices, determined by profiles created by retailers—profiles that individuals are likely unaware of, and even if accessible, might not align with their agreement.

1.2. PURCHASE INTENTION

Purchase Intention, defined by Fandos & Flavian (2006), signifies a consumer's anticipated behavior in short-term buying decisions. Price, as emphasized by Beneke et al. (2015), is a crucial factor influencing purchasing choices, representing the economic sacrifice consumers must make in transactions (Zeithmal, 1988). While generally higher prices correlate with lower purchase possibilities, researchers such Kara et al. (2009) argue that consumers don't uniformly view price negatively. Instead, price can serve as a complex signal of product quality, reflecting elegance and status.

However, AI-powered personalized pricing introduces a unique dynamic in e-commerce. According to Choi, Song, and Jing (2023), consumers often have negative views of price discrimination practices facilitated by advanced pricing algorithms, mainly due to perceived unfairness. Their research shows that the negative responses to price discrimination significantly affect consumer behavior, including spreading negative word of mouth and switching to competitors.

Supporting this, research by Bhagat et al. (2024) highlights that AI, through its human-like problem-solving abilities, can enhance decision-making capacities regarding purchase intention. However, as mentioned by Choi, Song, and Jing (2023) the perceived fairness and transparency of these AI-driven decisions are crucial, since their study indicates that

consumers' negative reactions to algorithm-driven price discrimination need addressing to mitigate adverse effects on purchase intentions.

Hypothesis 1 (H1): AI Pricing has a significant direct effect on Purchase Intention.

1.3. PRICE FAIRNESS

One of the most important concerns of the consumers regarding algorithmic pricing is their price fairness perception (Sahay, 2007). The perceived price fairness primarily depends on the amount of information that sellers unveil to the buyers (Choi and Mattila, 2009). According to Xia et al. (2004), price fairness is characterized as a consumer's evaluation and the corresponding emotions regarding whether the disparity between a seller's price and the price offered by a comparable alternative is reasonable, acceptable, or justifiable.

Pricing discrimination is a pricing strategy providing an individual or some segments of consumer groups with different prices (Elmaghraby and Keskinocak, 2003). Haws and Bearden (2006) found that when consumers find that they are paying more than other consumers, they experience a higher sense of price unfairness and lower perceived price fairness than they do when they encounter price differences across various stores and different times. This perceived price unfairness leads to increased perceived betrayal and public complaints and boycotts. Therefore, algorithmic price discrimination reflects firms' violations of the norms applicable to interactions with consumers, and it is an embodiment of their price fairness violation.

According to Choi, Song, and Jing (2023), addressing factors related to transparency and fairness in AI pricing can potentially alleviate negative consumer responses to price discrimination by AI algorithms. These findings suggest that improving transparency and fairness in AI-driven pricing practices is crucial to mitigate adverse effects on consumer purchase intentions.

Hypothesis 2 (H2): Price Fairness mediates the relationship between AI Pricing and Purchase Intention.

Hypothesis 3 (H3): Perceived fairness of AI-Pricing positively influences consumer trust in the pricing mechanisms employed by retailers in e-commerce.

1.4. TRUST

According to Garbarino & Lee (2003), trust plays a pivotal role in sustaining long-term relationships crucial for the success of businesses, particularly in the context of e-commerce. The impersonal nature of online transactions increases the significance of trust, given the limited cues available for its establishment. Urban, et al. (2000) underscore the critical role of trust in online purchase decisions, emphasizing its almost exclusive influence.

While the current study is focused on AI Pricing, past research on the effects of Dynamic Pricing on consumer trust by Garbarino & Lee (2003) provides relevant insights for research on AI pricing, on their study, they found that after a dynamic pricing event, people trust a company more in terms of goodwill rather than competence. This shift is influenced by how easily we can access and understand this goodwill trust. In sum, when prices change dynamically, we tend to focus more on whether the company seems trustworthy rather than how skilled it is. Also, when it comes to dynamic pricing, people react more strongly if it feels personally relevant, especially when they are offered higher prices. Those who feel disadvantaged by dynamic pricing, because it's personally relevant to them, are likely to react even more strongly than those who benefit. This heightened sensitivity to negative events, like higher prices, not only affects overall trust but also makes the importance of goodwill trust even stronger for customers facing higher prices.

Additionally, as noted by Hufnagel et al. (2022), consumers exhibit negative reactions to personalized pricing regardless of whether they benefit from it or not, further emphasizing the critical role of maintaining consumer's trust.

Hypothesis 4 (H4): Trust mediates the relationship between AI Pricing and Purchase Intention.

1.5. PRIVACY CONCERNS

Privacy concern, as described by Malhotra et al. (2004), reflects a user's worry about their information being revealed. This includes factors like data collection, errors, improper access, and secondary use, as outlined by Smith et al. (1996). Recognizing the connections between these factors, privacy concern is often evaluated as a second-order factor, as suggested by Stewart and Segars (2002).

When users have privacy concerns, they question if companies are gathering too much information and using it without their knowledge. This uncertainty and perceived risk associated with self-disclosure can significantly impact users' shopping intentions, leading to a decrease in their willingness to engage, as noted by Zhou (2020).

Hypothesis 5 (H5): Privacy Concern mediates the relationship between AI Pricing and Purchase Intention.

1.6. PRICE SENSITIVITY

Munnukka (2005) suggested that price sensitivity is one of the key factors in determining the selection of pricing in a company.

Research made by Peng et al. (2021) indicates that AI disclosure positively influences revenge behavior, with inferred negative motives mediating this impact. Notably, the study reveals a significant interaction effect between AI disclosure and price sensitivity, showing that consumers with high price sensitivity exhibit a greater increase in revenge behavior. Additionally, the presence of explanations for discriminatory pricing amplifies the impact of AI disclosure on revenge behavior, emphasizing the importance of contextual information. These results highlight the intricate dynamics at play, emphasizing the need for businesses to consider both AI disclosure and price sensitivity when crafting strategies to mitigate revenge behavior.

In this investigation, the study explores the moderating role of price sensitivity in the relationship between AI pricing and key consumer considerations: Fairness, Trust, and Privacy concerns. The research seeks to discern how variations in price sensitivity influence the impact of AI pricing on these critical dimensions of consumer perception.

Hypothesis 6a (H6a): Price sensitivity moderates the relationship between AI pricing and Fairness.

Hypothesis 6b (H6b): Price sensitivity moderates the relationship between AI pricing and Trust.

Hypothesis 6c (H6c): Price sensitivity moderates the relationship between AI pricing and Privacy concern.

1.7. CONCEPTUAL FRAMEWORK

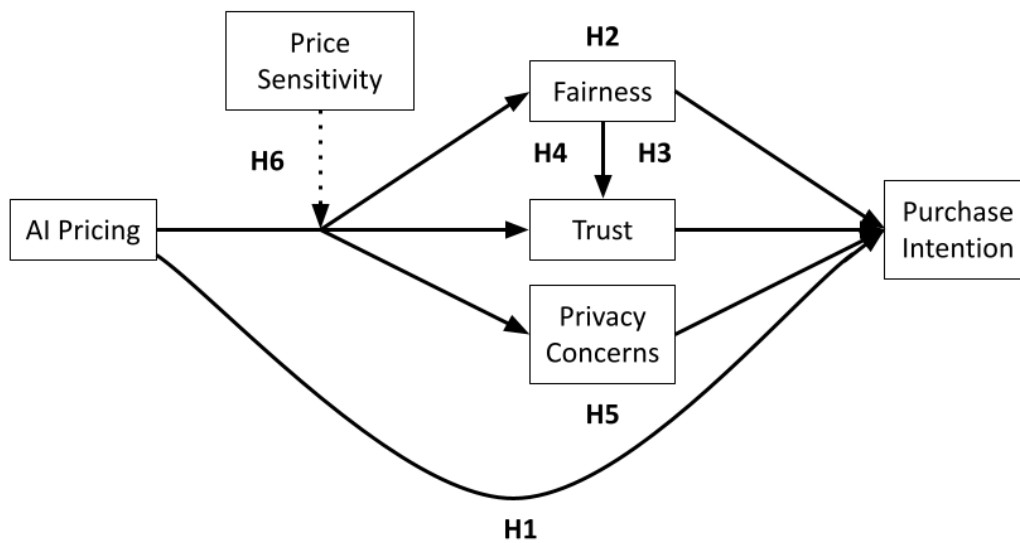


Figure 1- Conceptual Framework

The primary objectives of this research are threefold: firstly, to analyze the impact of AI-driven personalized pricing on consumer purchase intentions; secondly, to explore the moderating effects of individual factors, such as price sensitivity, on the relationship between personalized pricing and purchase intentions; and thirdly, to provide valuable insights into consumers' trust, perception of fairness, and privacy concerns surrounding AI-powered personalized pricing in e-commerce.

2. METHODOLOGY

2.1. RESEARCH DESIGN

The research design employed an experimental methodology to investigate and describe the nuances associated with consumer responses when faced with Normal Pricing versus AI-powered Pricing. The chosen design was motivated by the need to fill existing gaps in understanding the implications of AI-powered pricing strategies in shaping consumer purchase intentions. Specifically, the AI pricing scenario manipulated the information provided to participants: both groups saw the same prices, but the AI pricing group saw a disclaimer stating that the pricing was determined by AI, while the normal pricing group did not see any such disclaimer.

To rigorously assess and quantify the impacts of AI-powered personalized pricing, a quantitative approach was adopted. This methodology was well-suited for statistical analysis, facilitating the measurement of numerical data related to consumer responses. The goal was to draw meaningful insights and make statistical inferences regarding the influence of AI-powered pricing strategies on consumer purchase intentions.

To capture the diverse dimensions of consumer perceptions and behaviors, a survey was conducted. The survey instrument was meticulously designed to incorporate variables that reflected the essence of consumer decision-making when confronted with Normal Pricing versus AI-powered Pricing. This method allowed for the collection of valuable data on consumer attitudes, preferences, and purchase intentions.

Complementing the survey component, the study incorporated an experimental approach, a standard method for inferring causal relationships (Malhotra et al., 2017), in this case, between pricing strategies and consumer behavior. Experimental research enabled the manipulation of independent variables, in this case, the pricing strategies, to observe their direct impact on the dependent variable, consumer purchase intention.

A simple random sampling was implemented to ensure the validity of causal inferences. Consequently, each element in the population had an equal probability of being assigned to Normal Pricing or AI-powered Pricing conditions (Malhotra et al., 2017). This randomization helped control for potential confounding variables, ensuring that any observed differences in consumer responses were attributable to the specific pricing strategy rather than participant characteristics.

Given the prevalence of online interactions in the modern consumer landscape, the experimental component was conducted in Qualtrics. This approach maintained remote and anonymous interactions between the researcher and participants, mirroring real-world online shopping scenarios and enhancing the external validity of the findings by simulating a context where consumers often encounter pricing strategies.

Participants were recruited through Prolific, and they were paid a small amount to complete the survey. To ensure the relevance of the respondents, a screener was applied to filter for individuals who shop online at least once a month.

To ensure the proper manipulation and understanding of the experimental conditions, a pre-test was conducted. This pre-test verified that participants in both the AI-powered pricing and normal pricing conditions accurately perceived and understood the pricing strategies presented to them.

The research included two studies: Study 1 focused on televisions, while Study 2 focused on running shoes. These two different items were chosen to represent different price points and categories, allowing for a broader understanding of how AI-powered pricing influences consumer purchase intentions across various product types.

2.2. MEASURES

This research examined the influence of AI-powered pricing on consumer purchase intention. To do so, we proposed a research model which included the following constructs: AI Pricing, Price Sensitivity, Fairness, Trust, Privacy Concerns, and Purchase Intention.

AI Pricing was defined as the use of artificial intelligence and machine learning algorithms to analyze complex data patterns regarding customer behavior, market changes, competitor activity, and other relevant factors in real-time for optimal pricing and discounting (Takyar, 2023). To measure this construct, participants were exposed to scenarios simulating AI-powered pricing and Normal pricing. Therefore, the participants were questioned about their perception and evaluation of the displayed pricing strategies.

Moreover, price sensitivity referred to consumers' feelings regarding the payment of a specific price for a determined product (Ferreira et al., 2016). This construct was assessed using the Van Westendorp Price Sensitivity Scale (Ceylana et al., 2014), which allowed us to measure participants' perception of the value of the products or services. This measure was also crucial to analyze how individual differences in price sensitivity moderated the relationship between AI Pricing and fairness, trust, and privacy concerns.

Regarding fairness perception, it was considered the judgments of consumers regarding the price's justness, reasonableness, acceptability, and equitability (Martínez et al., 2013). To measure this construct, a scale used by Priester et al. (2020) and Martin et al. (2009) was implemented.

In respect to privacy concerns, it related to consumers' uncertainties about the privacy and security of their personal data (Robertson, 2019). Privacy concerns were evaluated through established privacy questions to understand participants' perceptions, adapted from Smith et al. (1996) and Dinev and Hart (2004).

Furthermore, trust concerns related to participants' confidence in the reliability and benevolence of the pricing strategy (Hufnagel et al., 2022). This construct was assessed through accepted scales to measure participants' benevolence trust, competence trust, and overall trust in the pricing system. The scale used was a 7-point Likert scale, adapted from Garbarino & Lee (2003).

Purchase intention represented participants' expressed likelihood to purchase based on the presented pricing strategy. Participants were asked to indicate their likelihood of making a purchase under the specific pricing conditions. The scale used was a 7-point Likert scale, adapted from Grewal et al. (1998).

In addition to the main constructs, two variables were included to ensure robustness and accuracy in measuring the effects of AI-powered pricing. Quality Perception was assessed using a 7-point Likert scale to measure participants' perceptions of product attractiveness and condition certainty. Algorithm Aversion, measured on a 0-100 scale, captured participants' trust in algorithms compared to human experts in determining product prices. These control variables were crucial to account for potential biases or external factors that could influence participants' responses to the main constructs.

Table 1– Table of Items

Variable	Items	Source
Price Sensitivity	(7-point Likert scale)/5-point 1. I am less willing to buy a new TV if I think it will be high in price. 2. I know that new TVs are likely to be more expensive than older ones, and that matters a lot to me. 3. In general, the price or cost of buying a new TV is important to me. 4. I mind paying more to try out a new TV model.	Goldsmith & Newell (1997)

Fairness Perception	(7-point Likert scales) 1. The price is fair. 2. The price is reasonable 3. The price is acceptable.	Priester et al. (2020) Martin et al. (2009)
Trust	(7-point Likert scales) 1. I feel that this store's pricing is reliable. 2. I feel that this store's pricing reflects competence in providing fair and reasonable prices. 3. I feel that this store's pricing demonstrates high integrity. 4. I feel that this store's pricing is responsive to customers' needs and preferences.	Sirdeshmukh et al. (2002)
Privacy Concerns	(7-point Likert scales) 1. When faced with this scenario, it bothers me that the store is able to track information about me. 2. When faced with this scenario, I am concerned that the store has too much information about me. 3. When faced with this scenario, it bothers me that the store is able to access information about me. 4. When faced with this scenario, I am concerned that my information could be used in ways I could not foresee.	Smith et al. (1996) Dinev and Hart (2004)
Purchase Intention	(7-point Likert scales) 1. I would purchase this TV. 2. I would consider buying at this price. 3. The probability that I would consider buying this TV is high.	Grewal et al. (1998)
Control Variables		

Quality Perception	(7-point Likert scale) 1. The product was visually attractive. 2. I am sure the product offered is in good condition.	Hanifati & Salehudin (2021)
Algorithm Aversion	(0-100 scale) 3. How much would you trust a very well qualified person to establish the price of this product? 4. How much would you trust an algorithm to establish the price of this product?	Castelo et al. (2019)
Manipulation Checks		
	How do you think the price was established? (5-point Likert scale) 1. The price was calculated by a Person. 2. The price was calculated by an Algorithm.	
	Based on the situation you just saw; do you believe the product was a result of: (Multiple choice) <ul style="list-style-type: none"> • Human Assessment • Artificial Intelligence assessment 	

3. DATA ANALYSIS

3.1. PRETEST

The pretest was held to check whether the conditions were perceived by the audience properly with full understanding what pricing strategy belonged to what pricing method. Results analysis was carried out with the help of SPSS. We recruited a group of 44 respondents on Prolific, the screening of participants included individuals located all around the world, who shop online more than once a month.

This manipulation impacted participants' views on the origin of pricing decisions ($F= 6.175$, $p= 0.017$). In the Normal Pricing group, respondents tended to believe that prices were determined by human calculation ($M= 1.39$, $SD= 0.499$) and the participants in the AI Pricing condition leaned towards AI assessment ($M= 1.74$, $SD= 0.449$).

Regarding the main effect on Purchase Intention, while not statistically significant ($F= 1.803$, $p= 0.186$), participants in the Normal Pricing condition showed a slightly higher purchase intention ($M= 4.580$, $SD= 1.57$) compared to those in the AI Pricing condition ($M= 3.956$, $SD= 1.58$).

Analysis of Trust revealed a significant effect ($F= 6.089$, $p= 0.018$), with individuals in the Normal Pricing condition exhibiting higher levels of trust ($M= 4.77$, $SD= 1.27$) compared to the AI Pricing group ($M= 3.9$, $SD= 1.11$).

Similarly, the effect on Fairness Perception approached significance ($F= 3.794$, $p= 0.058$), with participants in the Normal Pricing condition perceiving higher fairness ($M= 5.16$, $SD= 1.38$) than those in the AI Pricing condition ($M= 4.49$, $SD= 0.93$).

In contrast, the manipulation did not significantly influence perceptions of Privacy Concerns ($F= 0.007$, $p= 0.934$), with both groups showing similar mean scores (Normal Pricing: $M= 4.81$, $SD= 1.55$; AI Pricing: $M= 4.77$, $SD= 1.96$).

The manipulation performed as expected, allowing the smooth continuation of Study 1 without any modifications to the experimental setup or survey parameters.

3.2. STUDY 1

Descriptive Analysis

A total of 201 participants responded to the survey, with 103 participants engaging with the Normal Pricing Strategy scenario and 98 participants engaging with the AI Pricing Strategy scenario.

The gender distribution among the respondents was as follows:

Table 2– Study 1 Gender Distribution

Gender	Frequency	Percent
Female	88	43,8%
Male	108	53,7%
Non-binary / third gender	5	2,5%

The education level of the respondents varied between below High School and Doctoral Degree.

Table 3– Study 1 Education Level Distribution

Education Level	Frequency	Percent
Below High School	3	1.5%
High School	58	28.9%
Bachelor’s Degree	91	45.3%
Master’s Degree	43	21.4%
Doctoral Degree	4	2%

The age distribution of the respondents ranged from 19 to 71 years old (M= 31.09, SD= 10.18).

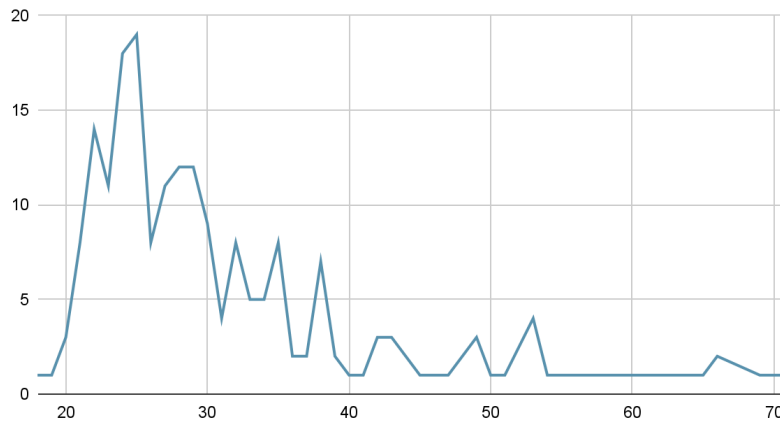


Figure 2- Study 1 Age Distribution

Regarding the online shopping habits, the participants make purchases online frequently ($M= 2.91$, $SD= 0.84$), they feel moderately confident on how algorithms impact pricing strategies in online shopping ($M= 2.70$, $SD= 1.096$) and are likely to compare prices across different websites before making an online purchase ($M= 4.48$, $SD= 0.80$).

Manipulation Check

The manipulation effectively influenced participants' perceptions of pricing establishment methods ($F= 83.97$, $p= <0.001$; $F= 45.66$, $p= <0.001$), as evidenced by significant differences between the two conditions. In the Normal Pricing group, respondents tended to believe that prices were determined by human calculation ($M= 3.13$, $SD= 1.026$), whereas in the AI Pricing group, participants were more inclined to perceive prices as determined by algorithms ($M= 4.42$, $SD= 0.973$).

This manipulation also impacted participants' views on the origin of pricing decisions ($F= 42.377$, $p= <0.001$). Those exposed to the Normal Pricing condition were more likely to attribute pricing decisions to human assessment ($M= 1.49$, $SD= 0.502$), while participants in the AI Pricing condition leaned towards AI assessment ($M= 1.88$, $SD= 0.329$).

Scale Reliability

We tested for Scale Reliability and the Alpha was acceptable for Purchase Intention ($\alpha=0.928$), for Trust ($\alpha=0.913$), for Fairness ($\alpha= 0.922$), for Privacy Concerns ($\alpha=0.958$) and for Price Sensitivity ($\alpha= 0.579$). We tested the reliability of the Quality Perception through Pearson Correlation, the result was 0.539, which indicates a moderate correlation.

3.2.1. Control Variables

Quality Perception

When comparing quality perception between the two groups, the normal pricing group had a mean score of 5.35 (SD= 1.02), while the AI pricing group had a mean score of 5.429 (SD= 0.984). The ANOVA results ($F= 0.273$, $p= 0.602$) indicate that the difference in quality perception between the two groups is not statistically significant. Therefore, the type of pricing scenario does not significantly affect consumers' perception of quality.

Algorithm Aversion

To understand the algorithm aversion we have included 2 items on a scale from 0 to 100: 1 for the participant to rate how much would the participant trust a well verified person to establish the price of the TV ($M= 70.59$, $SD= 18.713$), and a second one, to rate how much would the participant trust an algorithm to establish the price of the TV ($M= 53.99$, $SD= 24.85$).

When comparing algorithm aversion between the two groups, the normal pricing group had a mean score of -12.476 (SD= 29.526), while the AI pricing group had a mean score of -20.929 (SD= 28.618). The ANOVA results ($F= 4.241$, $p= 0.041$) indicate that the difference in algorithm aversion between the two groups is statistically significant. Data analyses were conducted with and without algorithm aversion as a covariate. Since there was no difference in the results, the results without covariates are reported here.

3.2.2. Hypothesis Testing

Main Effect

To test the main effect hypothesis, we used Analysis of Variance (ANOVA). The Individuals who saw the AI Pricing reported lower levels of Purchase Intention ($M=3.54$, $SD= 1.63$), than respondents who saw the Normal Pricing scenario ($M=4.42$, $SD= 1.63$). The t-test results were significant ($F= 15.049$, $p= <0.001$), therefore Hypothesis 1 was confirmed.

Direct Effect

To test the direct effect hypothesis, we used Analysis of Variance (ANOVA). The Individuals who perceived fairness of AI-Powered Pricing strategy positively influenced consumer trust in the pricing mechanisms employed, the results were significant ($F= 13.873$, $p= <0.001$), therefore Hypothesis 3 was confirmed.

Significant differences were observed between participants exposed to Normal Pricing and AI Pricing scenarios across key dimensions. Fairness perceptions yielded a significant effect ($F = 18.475, p < 0.001$), with higher scores reported in the Normal Pricing group compared to the AI Pricing group. Trust also showed a significant effect ($F = 26.627, p < 0.001$), favoring the Normal Pricing scenario. Similarly, privacy concerns were significantly affected ($F = 15.607, p < 0.001$), with higher scores reported in the AI Pricing group.

Table 4- Direct Effect by Dimension on Study 1

	<i>Group</i>	<i>Mean</i>	<i>Std. Deviation</i>
<i>Fairness Perception</i>	Normal Pricing	5.178	1.214
	AI Pricing	4.384	1.400
	Total	4.791	1.364
<i>Trust</i>	Normal Pricing	4.614	1.106
	AI pricing	3.679	1.449
	Total	4.158	1.365
<i>Privacy Concerns</i>	Normal Pricing	4.384	1.718
	AI Pricing	5.286	1.507
	Total	4.823	1.677

3.2.3. Mediation Analysis

To analyze mediation effects, we used PROCESS model 4, considering 5000 bootstrap samples.

Mediation Analysis of Fairness Perception

Path A from Scenario to Fairness Perception was significant ($b=-0.794, t= -4.298, p= 0.000$). Path B which tested the impact of Fairness Perception on Purchase Intention was significant ($b=0.825, t= 12.676, p= 0.000$). The total path from IV to DV was also significant ($b=-0.883, t=-3.879, p= 0.000$), however the direct path was not significant ($b=-0.228, t= -1.287, p= 0.200$) when we consider Fairness Perception in the model. The indirect effect of the mediator was significant ($b=-0.392, LLCI= -.566, ULCI= -.216$).

Therefore, hypothesis 2 was confirmed, indicating that fairness perception plays a negative mediating role in the relationship between AI pricing and purchase intention.

Mediation Analysis of Trust

Path A from Scenario to Trust was significant ($b=-0.936$, $t= -5.160$, $p= 0.000$). Path B which tested the impact of Trust on Purchase Intention was significant ($b= 0.882$, $t=13.898$, $p= 0.000$). The total path from IV to DV was also significant ($b=-0.883$, $t=-3.879$, $p=0.000$), however the direct path was not significant ($b=-0.058$, $t= -0.333$, $p= 0.739$) when we consider Trust in the model. The indirect effect of the mediator was significant ($b=-0.495$, $LLCI= -0.692$, $ULCI= -0.305$).

Therefore, hypothesis 4 was confirmed, indicating that Trust plays a negatively mediating role in the relationship between AI Pricing and Purchase Intention.

Mediation Analysis of Privacy Concerns

Path A from Scenario to Privacy Concerns was significant ($b=0.902$, $t= 3.950$, $p= 0.000$). Path B which tested the impact of Privacy Concerns on Purchase Intention was not significant ($b= -0.115$, $t= -1.637$, $p= 0.103$). The total path from IV to DV was significant ($b= -0.883$, $t= -3.879$, $p= 0.000$), the direct path was also significant ($b= -0.779$, $t= -3.310$, $p= 0.01$) when we consider Privacy Concern in the model. The indirect effect of the mediator was not significant ($b= -0.062$, $LLCI= -0.158$, $ULCI= 0.021$).

Therefore, hypothesis 5 was not confirmed.

3.2.4. Moderation Analysis

For the moderation analysis we used Model 1 of Process having the Scenario as Independent Variable, Price Sensitivity as the moderator variable and Fairness, Trust and Privacy as the Dependent Variables.

Fairness: The interaction of the moderating variable was not significant ($t= -0.3966$, $p= 0.6921$)

Trust: The interaction of the moderating variable was not significant ($t=-0.567$, $p= 0.5711$)

Privacy: The interaction of the moderating variable was not significant ($t= 0.0269$, $p= 0.9876$)

Therefore, Hypothesis 6a, 6b and 6c are not confirmed.

A moderated mediation test (Process's Model 7) was also performed, and the results were not significant, which confirms that there is no moderation of price sensitivity.

3.2.5. Discussion

The findings from Study 1 highlight several key insights into the impact of AI-powered pricing strategies on consumer behaviors and perceptions. Initially, our results confirm that exposure to AI pricing significantly diminishes purchase intention compared to scenarios involving normal pricing strategies. This outcome underscores the potential consumer apprehension and skepticism towards pricing decisions made by AI algorithms in e-commerce. Notably, perceptions of fairness played a crucial role, with participants in the normal pricing group consistently rating fairness higher than those exposed to AI pricing. This disparity suggests that while AI-driven pricing may offer efficiency benefits, it also risks compromising consumer trust and perceived fairness in pricing mechanisms.

The decision to conduct a second study arises from the need to validate and extend these findings in a different purchase context involving a lower-priced product. This approach aims to examine whether the observed effects persist across different consumer scenarios and price points, potentially influencing consumer responses to AI-calculated prices differently. By investigating a broader spectrum of consumer reactions to AI pricing in varied contexts, this study seeks to provide a comprehensive understanding of the implications of AI-powered pricing strategies in influencing consumer purchase intentions and perceptions.

3.3. STUDY 2

Study 2 aimed to extend the findings of Study 1 by examining the impact of AI-powered pricing on consumer behavior in a different purchase context: running shoes. This choice was deliberate to test the research model with a lower-priced product that typically involves less technical specifications compared to the TV used in Study 1. Running shoes also represent a common and routine purchase for many consumers, potentially influencing how pricing type affects consumer behavior.

Similar to Study 1, Study 2 utilized a between-subjects single-factor design where participants were randomly assigned to either an AI-powered pricing scenario or a control scenario (normal pricing). Data collection was again conducted on Qualtrics with participants from Prolific, utilizing screeners to ensure participants were regular online shoppers who purchase online at least once a month.

Descriptive Analysis

A total of 127 participants responded to the survey, with 64 participants engaging with the Normal Pricing Strategy scenario and 63 participants engaging with the AI Pricing Strategy scenario.

The gender distribution among the respondents was as follows:

Table 5– Study 2 Gender Distribution

Gender	Frequency	Percent
Male	55	43,3%
Female	72	56,7%

The education level of the respondents varied from High School to Doctoral Degree.

Table 6– Study 2 Education Level Distribution

Education Level	Frequency	Percent
High School	42	33.1%
Bachelor’s Degree	56	44.1%
Master’s Degree	27	21.3%
Doctoral Degree	2	1,6%

The age distribution of the respondents ranged from 19 to 68 years old (M= 32.24, SD= 10.298).

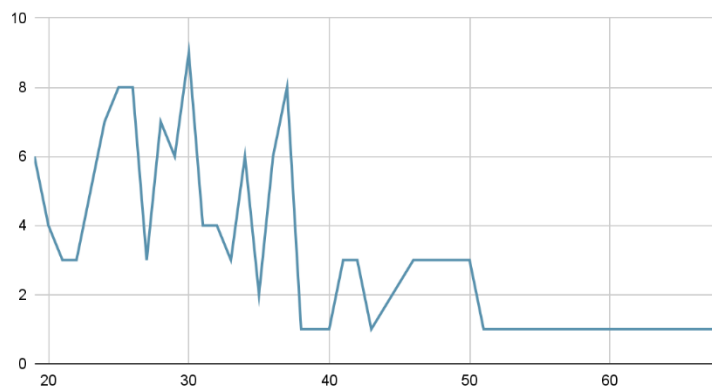


Figure 3- Study 2 Age Distribution

Regarding the online shopping habits, the participants make purchases online frequently (M= 3.02, SD= 0.63), they feel moderately confident on how algorithms impact pricing strategies in online shopping (M= 2.78, SD= 0.999) and are likely to compare prices across different websites before making an online purchase (M= 4.50, SD= 0.689).

Manipulation Check

The manipulation effectively influenced participants' perceptions of pricing establishment methods (F= 76.617, p= <0.001; F= 43.131, p= <0.001), as evidenced by significant differences between the two conditions. In the Normal Pricing group, respondents tended to believe that prices were determined by human calculation (M= 3.58, SD= 0.973), whereas in the AI Pricing group, participants were more inclined to perceive prices as determined by algorithms (M= 4.429 SD= 1.023).

This manipulation also impacted participants' views on the origin of pricing decisions (F= 54.020, p= <0.001). Those exposed to the Normal Pricing condition were more likely to attribute pricing decisions to human assessment (M= 1.30, SD= 0.460), while participants in the AI Pricing condition leaned towards AI assessment (M= 1.84, SD= 0.368).

Scale Reliability

We tested for Scale Reliability and the Alpha was acceptable for Purchase Intention (alpha=0.949), for Trust (alpha=0.933), for Fairness (alpha=0.935), for Privacy Concerns (alpha=0.942) and for Price Sensitivity (alpha=0.508). We tested the reliability of the Quality Perception through Pearson Correlation, the result was 0.436, which indicates a moderate correlation.

3.3.1. Control Variables

Quality Perception

When comparing quality perception between the two groups, the normal pricing group had a mean score of 4.92 (SD = 1.22), while the AI pricing group had a mean score of 5.079 (SD = 1.175). The ANOVA results (F = 0.495, p = 0.483) indicate that the difference in quality perception between the two groups is not statistically significant. Therefore, the type of pricing scenario does not significantly affect consumers' perception of quality.

Algorithm Aversion

To understand the algorithm aversion we have included 2 items on a scale from 0 to 100: 1 for the participant to rate how much would the participant trust a well verified person to establish the price of the TV (M=71.26, SD= 20.980), and a second one, to rate how much would the participant trust an algorithm to establish the price of the TV (M= 53.71, SD= 25.670).

When comparing algorithm aversion between the two groups, the normal pricing group had a mean score of -21.73 (SD = 29.594), while the AI pricing group had a mean score of -13.301 (SD = 31.545). The ANOVA results (F = 2.415, p = 0.123) indicate that the difference in algorithm aversion between the two groups isn't statistically significant.

3.3.2. Hypothesis Testing

Main Effect

To test the main effect hypothesis, we used Analysis of Variance (ANOVA). The Individuals who saw the AI Pricing reported lower levels of Purchase Intention (M=4.38, SD= 1.85), than respondents who saw the Normal Pricing scenario (M= 4.60, SD= 1.56). The t-test results were not significant (F= 0.539, p= 0.464), therefore Hypothesis 1 was not confirmed.

Direct Effect

To test the direct effect hypothesis, we used Analysis of Variance (ANOVA). The Individuals who perceived fairness of AI-Powered Pricing strategy positively influenced consumer trust in the pricing mechanisms employed, the results were significant (F= 10.341, p= <0.001), therefore Hypothesis 3 was confirmed.

Significant differences were observed between participants exposed to Normal Pricing and AI Pricing scenarios across key dimensions. Fairness perceptions did not yield a significant effect (F = 1.849, p = 0.176). Trust showed a moderate effect (F = 4.539, p = 0.035), favoring the Normal Pricing scenario. Similarly, privacy concerns were moderately affected (F = 4.056, p = 0.046), with higher scores reported in the AI Pricing group.

Table 7- Direct Effect by Dimension on Study 1

	<i>Group</i>	<i>Mean</i>	<i>Std. Deviation</i>
<i>Trust</i>	Normal Pricing	4.691	1.121
	AI pricing	4.155	1.668
	Total	4.425	1.439
<i>Privacy Concerns</i>	Normal Pricing	4.480	1.593
	AI Pricing	5.056	1.625
	Total	4.766	1.628

3.3.3. Mediation Analysis

To analyze mediation effects, we used PROCESS model 4, considering 5000 bootstrap samples.

Mediation Analysis of Fairness Perception

Path A from Scenario to Fairness Perception was not significant ($b=-0.325$, $t= -1.360$, $p= 0.176$). Path B which tested the impact of Fairness Perception on Purchase Intention was significant ($b=0.8449$, $t= 9.892$, $p= 0.000$). The total path from IV to DV was not significant ($b=-0.223$, $t=-0.734$, $p= 0.464$), and the direct path was also not significant ($b=0.051$, $t= 0.224$, $p= 0.8234$) when we consider Fairness Perception in the model. The indirect effect of the mediator was not significant ($b=-0.160$, $LLCI= -0.397$, $ULCI= 0.067$).

Therefore, hypothesis 2 was not confirmed.

Mediation Analysis of Trust

Path A from Scenario to Trust was significant ($b=-0.537$, $t= -2.130$, $p= 0.035$). Path B which tested the impact of Trust on Purchase Intention was significant ($b=0.840$, $t= 10.774$, $p= 0.000$). The total path from IV to DV was not significant ($b=-0.223$, $t=-0.734$, $p= 0.464$), also the direct path was not significant ($b=0.227$, $t= 1.018$, $p= 0.310$) when we consider Trust in the model. The indirect effect of the mediator was significant ($b=-0.263$, $LLCI= -0.518$, $ULCI= -0.028$).

Therefore, hypothesis 4 was confirmed, indicating that Trust plays a negatively mediating role in the relationship between AI Pricing and Purchase Intention.

Mediation Analysis of Privacy Concerns

Path A from Scenario to Privacy Concerns was significant ($b=0.575$, $t= 2.014$, $p= 0.046$). Path B which tested the impact of Privacy Concern on Purchase Intention was not significant ($b=-0.0178$, $t=-0.186$, $p= 0.853$). The total path from IV to DV was not significant ($b=-0.223$, $t= -0.734$, $p=0.464$), the direct path was also not significant ($b=-0.213$, $t= -0.687$, $p= 0.494$) when we consider Privacy Concern in the model. The indirect effect of the mediator was not significant ($b= -0.006$, $LLCI= -0.085$, $ULCI= 0.073$).

Therefore, hypothesis 5 was not confirmed.

3.3.4. Moderation Analysis

For the moderation analysis we used Model 1 of Process having the Scenario as Independent Variable and Fairness, Trust and Privacy as the Dependent Variables.

Fairness: The interaction of the moderating variable was not significant ($t= 1.405$, $p= 0.163$)

Trust: The interaction of the moderating variable was not significant ($t=0.009$, $p= 0.993$)

Privacy: The interaction of the moderating variable was not significant ($t= -0.495$, $p= 0.622$)

Therefore, Hypothesis 6a, 6b and 6c are not confirmed.

A moderated mediation test (Process's Model 7) was also performed, and the results were not significant, which confirms that there is no moderation of price sensitivity.

3.3.5. Discussion

Study 2 examined the impact of AI-powered pricing on consumer purchase intention across different product price points. Contrary to the findings from Study 1, H1 was rejected in Study 2. Although there was a small nominal difference in the average purchase intentions between those exposed to AI-determined prices and those who were not, this difference was not statistically significant. This indicates that AI-powered pricing did not significantly affect consumer purchase intentions in Study 2. A possible explanation for the absence of a significant main effect is that Study 2 considered a lower-priced product, leading to a purchase decision with less consumer involvement. Despite the difference in main effects, the mediation analyses in both studies yielded similar results.

Interestingly, while trust in pricing mechanisms emerges as a robust mediator in both studies, the role of fairness perceptions varies. In Study 1, fairness significantly mediated the relationship between AI pricing and purchase intention, indicating its importance in higher-

priced purchases. However, in Study 2 focusing on a lower-priced product, fairness perceptions did not significantly influence purchase intention. This suggests that for everyday purchases, fairness may not be as decisive in consumer decision-making.

The consistent lower levels of trust associated with AI pricing mechanisms across both studies highlight a key factor driving consumer reluctance. This lack of trust may stem from concerns over transparency, algorithmic bias, or the perceived absence of human oversight in pricing decisions.

Moreover, the non-significant moderation effects of price sensitivity indicate that individual differences in price sensitivity do not significantly alter consumer responses to AI pricing. This suggests that while consumers may vary in their sensitivity to price changes, AI pricing strategies uniformly impact trust and purchase intention regardless of these differences.

4. RESULTS AND DISCUSSION

4.1. THEORETICAL CONTRIBUTIONS

This study provides valuable insights into the influence of AI-powered pricing strategies on consumer behavior, affirming the significant roles of trust and perceived fairness in shaping purchase intention. These findings align with prior research on price fairness (Xia et al., 2004) and trust (Garbarino & Lee, 2003). Recent studies by Choi, Song, and Jing (2023), Wang et al. (2022), and Hufnagel et al. (2022) highlight the negative consumer perceptions of algorithm-driven price discrimination due to perceived unfairness and the critical role of trust. Peng et al. (2021) further emphasize the importance of transparency, noting that AI disclosure can influence revenge behavior. These contemporary insights underscore the need for transparency and fairness in AI-driven pricing to improve consumer purchase intentions.

Traditional pricing strategies, perceived as transparent and under human control, foster higher levels of consumer trust and fairness perceptions compared to AI-powered pricing strategies. This observation underscores the enduring importance of human oversight and intervention in pricing decisions, which contemporary consumers still value amidst advancements in AI technology.

Moreover, the study unveils a marked aversion to AI-powered pricing, with participants strongly preferring prices set by humans. This preference significantly influences purchase intentions, reflecting persistent consumer skepticism towards algorithmic pricing models despite their potential efficiency and benefits. This finding resonates with ongoing discussions on the ethical implications and public apprehensions surrounding algorithmic decision-making (Turow, 2017).

In addition, mediation analyses highlight the critical roles of fairness and trust as mediators between pricing strategy and purchase intention. The significant indirect effects underscore the pivotal influence of perceived fairness and trust in shaping consumer behavior across diverse pricing contexts. This consistency with previous research emphasizes the enduring impact of fairness perceptions (Sahay, 2007; Xia et al., 2004) and trust (Garbarino & Lee, 2003) on consumer responses to pricing strategies.

This study diverges from Hufnagel, Schwaiger, and Weritz (2022) by focusing on the broader impacts of AI-powered pricing strategies across different product contexts, rather than personalized pricing effects based on individual consumer characteristics. Unlike Choi, Song, and Jing (2023), which explore algorithmic cues in hospitality, this study contributes to a comprehensive understanding of AI pricing strategies' effects on consumer behavior across different e-commerce sectors.

The theoretical contribution lies in elucidating how trust and fairness perceptions underpin consumer acceptance of AI-powered pricing strategies. By revealing persistent consumer

preferences for human-controlled pricing and identifying the mediating roles of fairness and trust, this study enriches our understanding of consumer responses to technological innovations in pricing. This insight is crucial for policymakers and businesses navigating the ethical and operational implications of AI adoption in pricing strategies.

In summary, this research extends our comprehension of how AI-powered pricing strategies influence contemporary consumer behavior. Despite technological advancements, consumer preferences for transparency and human involvement in pricing decisions remain paramount. Future research should continue exploring evolving consumer attitudes towards AI technologies to inform ethical and effective implementation strategies in pricing contexts.

4.2. MANAGERIAL CONTRIBUTIONS

Enhancing Trust in AI Pricing

From a management perspective, companies should focus on strategies to build consumer trust in AI-Powered pricing. Reflecting Garbarino & Lee's (2003) emphasis on trust, transparent communication about how AI algorithms determine prices and the benefits to consumers can mitigate trust issues and enhance acceptance.

Emphasizing Fairness

Ensuring perceived fairness in AI-powered pricing showed to be essential, which is consistent with the literature on fairness concerns (Sahay, 2007; Xia et al., 2004), businesses should develop AI algorithms that consider fairness and transparency. Incorporating mechanisms that allow consumers to understand and feel comfortable with how prices are determined can help improve perceived fairness and trust.

Reduce Algorithm Aversion

To combat algorithm aversion, companies could provide options for consumers to choose between AI and human-driven pricing. Educating consumers about the benefits and accuracy of AI pricing can help reduce skepticism, as highlighted by Turow (2017). Offering a choice may empower consumers and increase their acceptance of AI-driven pricing.

Consumer Segments Tailored Pricing Strategies

The findings indicate that different consumer segments might respond differently to AI pricing. Companies should consider segmenting their marketing strategies based on consumer preferences for AI versus human-driven pricing to maximize engagement and sales. This

approach is consistent with the diverse consumer responses to pricing strategies discussed in the literature.

Reducing Privacy Concerns in E-commerce

To reduce privacy concerns in e-commerce, companies should implement robust data protection measures and communicate these efforts clearly to consumers. Providing transparent information about data usage, securing consumer data, and ensuring compliance with privacy regulations can help alleviate consumer fears. Emphasizing the steps taken to protect consumer information can build trust and make consumers more comfortable with AI-powered pricing.

4.3. LIMITATIONS AND FUTURE RESEARCH

Despite its contributions, this study has several limitations that present opportunities for future research. The study's sample was diverse but limited to individuals who shop online frequently. Future research could explore how less frequent online shoppers or those from different demographic backgrounds respond to AI pricing strategies. This broader demographic research can provide a more comprehensive understanding of consumer behavior across various segments.

Consumer perceptions of AI pricing might evolve over time. Longitudinal research could provide insights into the long-term acceptance and trust in AI-driven pricing.

Since the products from Study 1 and Study 2 belong to different categories, future research could investigate how contextual factors, such as product type, influence consumer responses to AI pricing. Understanding these distinctions can help companies adapt their pricing strategies more effectively.

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0298

APPENDIX A- SURVEY

Start of Block: intro

intro Welcome to our survey!

The following questionnaire is made for academic research purposes, and its aimed at understanding consumer responses to different pricing strategies. We're interested in learning more about how consumers perceive and react to various pricing methods.

The estimated time for completing this questionnaire is about 4 minutes.

By responding to this survey, you confirm that you are over the age of 18. Your participation in this survey implies that you meet the legal age requirements to provide consent for data collection and analysis. If you are under 18 years old, please refrain from participating in this survey.

If you have any questions, don't hesitate to get in touch with 20220357@novaims.unl.pt

Thank you for your attention and collaboration.

End of Block: intro

Start of Block: normal_price

NormalPrice Imagine yourself browsing an online electronics store for a new TV.

You land on a product page showcasing a high-definition television with a price tag that seems reasonable.

Please answer the following questions with this scenario in mind.

End of Block: normal_price

Start of Block: ai_price

Imagine yourself browsing an online electronics store for a new TV.

You land on a product page displaying a high-definition television with a price tag that seems reasonable, but something catches your eye – the price is personalised to you by an AI algorithm.

Please answer the following questions with this scenario in mind.

End of Block: ai_price

Start of Block: manipulation_check



manipulation_check1 How do you think the price was established?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree or disagree (3)	Somewhat agree (4)	Strongly agree (5)
The price was calculated by a Person. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The price was calculated by an Algorithm. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page Break



manipulation_check2 Based on the situation you just saw, do you believe the price of the product was a result of:

- Human assessment (1)
- Artificial Intelligence assessment (2)



Page Break

manipulation_check3 How much do you think the price was personalised to you?

- Not personalised at all (1)
- Slightly personalised (2)
- Moderately personalised (3)
- Highly personalised (4)
- Extremely personalised (5)

End of Block: manipulation_check

Start of Block: main_block



FairnessConcerns Consider the scenario you've just seen and tell us how much you agree with these statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
The price is fair. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The price is reasonable. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The price is acceptable. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Trust Consider the scenario you've just seen and tell us how much you agree with these statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I feel that this store's pricing is reliable. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this store's pricing reflects competence in providing fair and reasonable prices. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this store's pricing demonstrates high integrity. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that this store's pricing is responsive to customer's needs and preferences. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

PurchaseIntention Consider the scenario you've just seen and tell us how much you agree with these statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I would purchase this TV. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would consider buying this TV at this price. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
The probability that I would consider buying this TV is high. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

 Page Break

PrivacyConcerns Consider the scenario you've just seen and tell us how much you agree with these statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
When faced with this scenario, it bothers me that the store is able to track information about me. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
When faced with this scenario, I am concerned that the store has too much information about me. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

When faced with this scenario, it bothers me that the store is able to access information about me. (3)

When faced with this scenario, I am concerned that my information could be used in ways I could not foresee. (4)



Page Break

PriceSensitivity Consider the scenario you've just seen and tell us how much you agree with these statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am less willing to buy a new TV if I think it will be high in price. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I know that new TVs are likely to be more expensive than older ones, and that matters a lot to me. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
In general, the price or cost of buying a new TV is important to me. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

I mind paying more to try out a new TV model.
(4)

End of Block: main_block



Start of Block: control_variables

QualityPerception Consider the scenario you've just seen and tell us how much you agree with these statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
The product was visually attractive. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am sure the product offered is in good condition. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

AlgorithmAversion Considering what you've just seen:

0 10 20 30 40 50 60 70 80 90 100

How much would you trust a very well qualified person to establish the price of this TV? ()	
How much would you trust an algorithm to establish the price of this TV? ()	

End of Block: control_variables

Start of Block: additional_questions

aq1 How often do you make purchases online?

- Rarely (1)
- Occasionally (2)
- Frequently (3)
- Very frequently (4)

Page Break

aq2 How confident are you in your understanding of how algorithms impact pricing strategies
in online shopping?

- Not confident (1)
- Slightly confident (2)
- Moderately confident (3)
- Confident (4)
- Very confident (5)

Page Break

aq3 How likely are you to compare prices across different websites before making an online purchase?

- Very unlikely (1)
- Unlikely (2)
- Neutral (3)
- Likely (4)
- Very likely (5)

End of Block: additional_questions

Start of Block: demographic

Gender Gender

- Male (1)
- Female (2)
- Non-binary / third gender (3)
- Prefer not to say (4)



Age

Age



Education

Education

Level

- Below High School (1)
- High School (2)
- Bachelor's Degree (3)
- Master's Degree (4)
- Doctoral Degree (5)
- N/A (0)

End of Block: demographic

APPENDIX B- PRE-TEST AND STUDY 1 MANIPULATION

SMART TV 4K 55'



399€

Add to Cart

1- Normal Pricing Group

SMART TV 4K 55'



399€

Price personalised to you by an AI algorithm

Add to Cart

2- AI Pricing Group

APPENDIX C- STUDY 2 MANIPULATION



Running Shoes



39€

Add to Cart

1- Normal Pricing Group



Running Shoes



39€

Price personalised to you by an AI algorithm

Add to Cart

2- AI Pricing Group



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