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Algorithmic Pricing and Fairness: A Moderated Moderation Model of AI Disclosure and Typicality of AI Pricing

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Abstract

In the era of big data, the utilization of algorithms for dynamic pricing has become prevalent. However, concerns have been raised about the potential negative impact of these practices on consumers' fairness perceptions. Using attribution theory as the underlying framework, we explore how AI disclosure moderates the relationship between AI pricing type (unified/personalized dynamic pricing) and fairness perceptions (procedural/distributive fairness) and how this moderation effect is further moderated by the perceived typicality of AI pricing. An online scenario-based experiment was carried out with 145 participants. The results reveal that personalized dynamic pricing elicits lower fairness perceptions than unified dynamic pricing. Furthermore, we observe a significant moderated moderation effect, indicating that the negative impact of personalized dynamic pricing can be mitigated by AI disclosure for consumers who perceive AI pricing as typical. These findings contribute to AI pricing literature and the development of fairer platform designs.

Keywords: Dynamic pricing, AI disclosure, typicality of AI pricing, fairness

Introduction

Algorithmic pricing, also called artificial intelligence (AI) pricing, is a pricing mechanism that relies on computer algorithms to dynamically establish prices for goods and services (Seele et al., 2021). These algorithms analyze input data about the market and consumers, considering factors such as competitor prices, consumer demand, and individual behavior and characteristics (e.g., gender, age, educational background). The ultimate goal is determining an output price that maximizes profit by setting it relative to the highest attainable income (Cohen et al., 2018; Fisher et al., 2018). Algorithmic pricing manifests in two distinct forms: unified dynamic pricing and personalized dynamic pricing. Unified dynamic pricing, also known as real-time pricing, entails flexible price adjustments in response to uncertain market conditions to achieve revenue growth. Under this approach, prices remain consistent for each customer. Conversely, personalized dynamic pricing involves targeted pricing based on personal preferences and behaviors, representing a pricing strategy in which enterprises charge varying prices to different consumers based on their willingness to pay.

The advancement of AI technologies, including machine learning and deep learning, has led to increased complexity in algorithmic pricing, as opposed to previous simplistic if-then procedures (e.g., increasing the price of Coca-Cola if the temperature is above 20 °C) (Calvano et al., 2019). Pricing algorithms utilizing machine learning methods excel at predicting future demand and discerning patterns in individuals' willingness to pay (Miklós-Thal & Tucker, 2019). Additionally, in the era of big data, internet platforms have the capacity to charge varying prices to users by leveraging data advantages and information asymmetry. Through digital tracking via "cookies," companies can analyze consumer behavior, decipher individual characteristics and preferences, and engage in near-perfect price discrimination by identifying customers' reservation prices and willingness to pay (Ezrachi & Stucke, 2016). Consequently, the utilization of algorithms for personalized dynamic pricing has become a prevalent strategy among numerous businesses (Chen et al., 2016). Personalized dynamic pricing has emerged and continues to persist in various online marketplaces, encompassing domains such as online travel, online ticketing, online shopping, transportation, online video, and others (Edelman et al., 2017). For instance, CVS pharmacies often distribute targeted coupons to enhance in-store footfall (Zhang et al., 2016). The practice of personalized dynamic pricing is progressively gaining traction across diverse industries.

However, the implementation of dynamic pricing entails both advantages and disadvantages. On the one hand, dynamic pricing can benefit corporations in terms of revenue and profit growth to a certain extent (Fisher et al., 2018; Waldfogel, 2015). On the other hand, consumers often perceive dynamic pricing, particularly personalized dynamic pricing, as unfair or manipulative, leading to a decrease in trust toward companies and a reluctance to make purchases (Zuiderveen Borgesius & Poort, 2017). Observing that they are paying more than their peers can evoke a strong sense of unfairness among consumers. An incident reported in China exemplifies this sentiment, where a consumer expressed dissatisfaction online after discovering that the hotel room they previously booked for 380 RMB per night on Ctrip was priced at only 300 yuan when using a friend's account. Many other consumers shared similar experiences, providing evidence and criticizing e-commerce platforms for engaging in price discrimination practices (Zhang et al., 2022). A recent survey in the United States revealed that 71% of consumers disapproved of personalized dynamic pricing (Baird, 2017). It is vital for businesses to acknowledge the negative consequences of personalized dynamic pricing on consumer perceptions of fairness. Failing to address this impact can result in diminished consumer satisfaction and trust, incite market dissatisfaction, escalate competition, and ultimately harm corporate profits (Chen & Cui, 2013; Richards et al., 2016). Therefore, it is crucial for sellers to comprehend the influence of personalized dynamic pricing on consumer fairness perceptions and adapt their strategies accordingly.

In a society that heavily relies on algorithms, implementing blanket regulations or outright bans to address the adverse effects of pricing algorithms may not be practical (Bar-Gill et al., 2019). As a result, practitioners must adopt a proactive approach to mitigate the negative impacts of algorithmic pricing, particularly personalized dynamic pricing. There is a growing demand for regulations that require companies to disclose their use of AI, as consumers have a right to be aware of being monitored by algorithms or AI systems (MacCarthy, 2020). However, the influence of AI disclosure on dynamic pricing is still uncertain. Previous studies have yielded mixed findings, with some indicating positive effects of AI disclosures (Garvey et al., 2023; Hohenstein & Jung, 2020) and others suggesting negative effects (Luo et al., 2019) in different contexts. Understanding whether AI disclosure can alleviate the negative impact of personalized dynamic pricing is an important question that warrants further research. While previous studies have identified price framing strategies, external references, and additional gifts as potential mitigating factors for perceptions of unfairness in dynamic pricing (Weisstein et al., 2013), there is limited literature investigating the influence of AI disclosure on consumers' fairness perceptions of algorithmic pricing. Therefore, our study aims to bridge this research gap by examining the effect of AI disclosure in the context of algorithmic pricing.

Furthermore, while previous studies have primarily focused on situational factors that influence the impact of AI disclosure, it is essential to recognize that consumer characteristics themselves can also affect the effectiveness of AI disclosure. We posit that perceived typicality, which refers to how common and ordinary consumers perceive AI pricing to be, is a critical factor to consider. As knowledge and understanding of AI pricing and price discrimination strategies continue to develop, societal and industry norms evolve correspondingly. Awareness of differential pricing strategies may also play a significant role in shaping consumer responses (Pillai & Kumar, 2012). However, no prior research has examined how the perceived typicality of AI pricing influences consumer reactions. Our study aims to fill this research gap by investigating the moderating role of the perceived typicality of AI pricing in shaping the effects of AI disclosure in the context of algorithmic pricing.

This study examines how AI disclosure moderates the relationship between AI pricing type and fairness perceptions and how this moderation effect is further moderated by the perceived typicality of AI pricing. We hypothesize that personalized dynamic pricing is perceived as more unfair than unified dynamic pricing. Drawing on previous research on the impact of AI disclosure on subjective perceptions (Luo et al., 2019; Tong et al., 2021), we propose that AI disclosure attenuates the negative effect of personalized (vs. unified) dynamic pricing on fairness perceptions. We also expect that the positive impact of AI disclosure in personalized dynamic pricing is stronger when consumers perceive AI pricing as more typical. We test our moderated moderation model in a scenario-based experiment with 145 online participants in the context of online airline ticket booking, a common setting where algorithmic pricing is applied (Shukla et al., 2019). We use multivariate analysis of variance (MANOVA) and multiple regression analysis to analyze the data. This study advances the understanding of consumers' perceptions of algorithmic pricing in online marketplaces and offers practical implications for managers to design effective pricing strategies to enhance price fairness perceptions.

The paper is organized as follows. First, we review the relevant literature on dynamic pricing, AI disclosure, and perceived typicality. Second, we develop our theoretical background and hypotheses based on the attribution theory. Third, we describe our research method, including the experimental design, measures, and procedures. Fourth, we report our results and conduct a series of analyses to test our hypotheses. Fifth, we discuss our findings, implications, limitations, and directions for future research.

Literature Review

Dynamic Pricing

Previous research has highlighted the dual nature of dynamic pricing. On the one hand, the implementation of dynamic pricing can yield advantages for corporate revenue and profit growth to some extent (Fisher et al., 2018; Waldfogel, 2015). Additionally, dynamic pricing has the potential to increase social welfare. In a perfectly competitive environment, these benefits would eventually be transferred to consumers, resulting in lower market prices, increased consumer surpluses, and increased taxation by local and state governments, benefiting society as a whole (Faruqui & Palmer, 2011). On the other hand, consumers often perceive dynamic pricing, especially personalized dynamic pricing, as unfair, leading to a decrease in their trust in companies and their willingness to make purchases (Zuiderveen Borgesius & Poort, 2017).

Ethical concerns and fairness perceptions related to unified dynamic pricing have received less attention. Prior literature has found that consumers can detect dynamic pricing when the offered prices significantly deviate from their internal or external reference prices (Garbarino & Lee, 2003). Such price discrepancies may result in negative effects, including reduced future purchase intentions, decreased trust, or an increased likelihood of complaints (Garbarino & Maxwell, 2010). In contrast to unified dynamic pricing, the ethical concerns and unfairness perception of personalized pricing have sparked broader public and academic debates (Choe et al., 2018). As a form of price discrimination, personalized dynamic pricing is often regarded as unfair, leading to more significant negative consequences than unified dynamic pricing (Seele et al., 2021). Consumers may experience a strong sense of unfairness when they realize that they are paying more than their peers. No seller can afford to overlook the adverse impact of consumer unfairness caused by personalized dynamic pricing, as it can reduce consumer utility and trust, arouse market anger, intensify market competition, and ultimately harm corporate profits (Chen & Cui, 2013; Richards et al., 2016). Regarding personalized pricing, factors such as interpersonal price differences, perceived violations of social norms, and price frames are particularly relevant. When personalized dynamic pricing is disclosed, and consumers become aware that they are paying significantly higher prices than their peers, such practices are perceived as unfair or manipulative, leading to reduced trust and demand (Zuiderveen Borgesius & Poort, 2017). Previous research has conducted limited comparisons between the perceived fairness of personalized dynamic pricing and unified dynamic pricing. Furthermore, there is a lack of studies investigating how to mitigate the negative effects of personalized dynamic pricing.

Ways to Increase Fairness Perceptions

Prior literature suggests that employing price-framing strategies can mitigate perceptions of unfairness and increase customer trust in firms (Weisstein et al., 2013). One effective way to mitigate this negative perception is by providing an external reference to the price or offering additional gifts (Lee & Monroe, 2008). Specially targeted coupons displayed in the form of discounts have been identified as an effective framing strategy that masks personalized dynamic pricing (Tanner, 2014). In an online setting, very popular sites such as Ebates or Mr. Rebates are based on a cashback model, offering two asymmetric prices, thereby exploiting both promotion and price discrimination (Ho et al., 2017). It has also been demonstrated that firms can successfully address peer-induced fairness issues by obfuscating prices to discourage interpersonal comparisons and improve consumers' chances of accepting the prices offered (Allender et al., 2021). However, such price-framing tactics raise certain ethical challenges because they could be seen as misleading or manipulating consumers. Therefore, more ethical strategies are needed to enhance consumers' fairness perceptions and reduce the negative effect of personalized dynamic pricing.

The Effect of AI Disclosure

Previous studies have yielded contrasting findings regarding the effects of AI disclosure in different situations. For instance, in the context of structured outbound sales calls, AI disclosure has been found to have a significant negative effect on customers' purchase rates, resulting in a decrease of 79.7% (Luo et al., 2019). This negative impact of AI disclosure is attributed to a subjective human perception that AI is less knowledgeable and empathetic. Conversely, in situations where the offered price for a second-hand performance ticket or ride service is lower than expected, AI disclosure has been shown to have a positive effect on consumer responses due to AI's perceived weaker selfish intention (Garvey et al., 2023). Additionally, research has indicated that the use of AI smart replies in communication can enhance perceived trust, as AI functions as a "moral crumple zone" and reduces the responsibility attributed to human counterparts (Hohenstein & Jung, 2020). These studies demonstrate that AI disclosure can have varying effects on customer interactions. However, the specific influence of AI disclosure on consumers' fairness perceptions of personalized dynamic pricing relative to unified dynamic pricing in the context of algorithmic pricing remains unknown. Further investigation is needed to determine how AI disclosure impacts consumers' perceptions of fairness in personalized dynamic pricing compared to unified dynamic pricing.

Perceived Typicality

Throughout history, the development of new technologies has followed a pattern of questioning, understanding, acceptance, and maturity. Perceived typicality refers to the perception that a particular technology is common and ordinary. Previous studies have indicated that individuals with higher levels of perceived typicality are more familiar with and aware of new technologies, leading to reduced resistance towards them. These individuals are more inclined to accept the existence of new technology and have confidence in its potential (Orlikowski & Scott, 2014). For instance, in the case of robo-advisors, research has shown that individual differences in the perceived typicality of robotic systems play a crucial role in their adoption (Young et al., 2009). In the context of AI-related technologies, customers with higher levels of perceived typicality tend to place more excellent value on their attitudes and perceptions of usefulness. Conversely, consumers with lower levels of perceived typicality rely more heavily on subjective norms in their decision-making (Belanche et al., 2019). Studies on personalized dynamic pricing have found that the perception of a practice as more typical, based on its widespread use or longer-term implementation within an industry, contributes to a more excellent perception of equity (Kuo et al., 2016). However, previous studies have not examined the influence of the perceived typicality of AI pricing on shaping the impact of AI disclosure. This research gap highlights the need to investigate how the perceived typicality of AI pricing plays a role in shaping the effects of AI disclosure.

These studies have made significant contributions to the existing literature. However, our research distinguishes itself in several key aspects. Firstly, we contribute to the fairness literature on dynamic pricing by comparing the perceived fairness of personalized and unified dynamic pricing, as well as exploring strategies to mitigate the negative effects of personalized dynamic pricing. Secondly, we contribute to the AI disclosure literature by examining how AI disclosure affects consumers' perception of fairness in personalized dynamic pricing compared to unified dynamic pricing within the context of dynamic pricing. Lastly, we fill a research gap by investigating the role of the perceived typicality of AI pricing in shaping the impact of AI disclosure, an aspect that has not been explored in previous studies.

Theoretical Background and Hypotheses

Dynamic Pricing Type and Fairness Perceptions

In the context of dynamic pricing, where prices often increase, there has been extensive research examining people's perception of price fairness, particularly in situations involving price increases (Richards et al., 2016). Furthermore, personalized dynamic pricing, where an individual's price is worse than that of others, is more likely to elicit perceptions of unfairness (Hufnagel et al., 2022; van Boom et al., 2020). Therefore, the focus of our study revolves around price increases in dynamic pricing and situations where an individual's price is worse than that of others in personalized dynamic pricing. Weiner (1992) proposed an enduring causal attribution consequence model, which points out that locus, stability, and controllability are three attribution dimesons. This model has been successful in explaining consumers' responses to product failures (Folkes, 1984) and provides a valuable framework for understanding consumers' causal inferences regarding observed price increases. Previous studies have provided empirical evidence supporting the notion that even if price increases are justified by costs, they are perceived as less fair when consumers attribute the causality internally to the companies or believe that the companies have control over the price increases (Vaidyanathan & Aggarwal, 2003).

According to this study, Weiner's attribution theory can elucidate the mechanism by which different types of dynamic pricing (unified dynamic pricing and personalized dynamic pricing) influence consumers' fairness perceptions. Consumers engage in various comparisons to assess the reasonableness of prices, and the outcomes of these comparisons directly impact their fairness perceptions (Ferguson et al., 2014). When consumers become aware of personalized dynamic pricing and discover that they are being charged a higher price than others, they attribute this difference to enterprises pursuing profit maximization and engaging in price discrimination. As a result, consumers assign higher levels of internal attribution and controllability attribution, leading to a lower perception of price fairness (Kahneman et al., 1986).

However, when consumers recognize that pricing is dynamic but uniformly applied to all customers, they believe that enterprises adjust prices reasonably based on market conditions and the dynamics of supply and demand. This understanding results in lower levels of internal attribution and controllability attribution (Campbell, 1999). Such attributions lead consumers to view price increases as reasonable and justified by costs, making them more acceptable and contributing to higher fairness perceptions.

Therefore, the following hypothesis is proposed:

H1: When prices are increased, personalized dynamic pricing leads to consumers' lower fairness perceptions than unified dynamic pricing.

The Effect of AI Disclosure

We posit that the potential negative impact of personalized dynamic pricing can be alleviated through the implementation of AI disclosure. Previous research suggests that when AI disclosure is employed, consumers tend to respond more positively when they encounter a situation that is worse than expected, as AI presence reduces negative attributions toward firms (Garvey et al., 2023; Hohenstein & Jung, 2020). In the context of personalized dynamic pricing, individuals often receive price offers that are less favorable compared to others. Thus, we hypothesize that the introduction of AI disclosure is likely to enhance consumers' fairness perception of personalized dynamic pricing while potentially having no impact on their fairness perceptions of unified dynamic pricing.

Indeed, the absence of AI disclosure may lead consumers to attribute the price outcome in personalized dynamic pricing to the firm's selfish or intentional profit maximization. However, with the introduction of AI disclosure, consumers are less likely to make such negative attributions because AI is not perceived as having self-generated subjective intentions, motivations, or irrational behaviors (Wojciszke et al., 2009). As a result, AI is not judged as a moral subject deliberately acting with self-interest. When explaining dynamic pricing, the disclosure of price changes being caused by the AI pricing algorithm helps consumers understand that the relatively high price is determined by the AI. Since AI does not possess self-interest motivations or desires to fulfill private interests, it acts as a shield against the perceived deliberate motives of enterprises in pursuing profit maximization (Garvey et al., 2023). Consumers may subjectively perceive this as AI behavior without subjective intentions or self-awareness. They attribute the price difference with others to algorithmic computations based on big data rather than attributing it to the greed or other internal motives of the companies. Consequently, their perception of price fairness tends to be relatively high (Bigman et al., 2023).

However, in the case of unified dynamic pricing, where consumers face the same pricing situation as expected, the presence or absence of AI disclosure is unlikely to bring about significant changes in consumers' fairness perceptions. By incorporating AI disclosure, the negative disparity between AI pricing type and fairness perception is expected to diminish.

Therefore, this study puts forward this hypothesis:

H2: AI disclosure moderates the relationship between pricing types and fairness perceptions such that with the presence of AI disclosure, the negative effect of personalized (vs. unified) dynamic pricing on fairness perceptions would be less prominent.

The Moderating Effect of Typicality of AI Pricing on AI Disclosure

Perceived typicality refers to the extent to which individuals perceive a particular technology as common and customary. Individuals with high perceived typicality possess greater familiarity and awareness of new technologies, leading them to exhibit reduced resistance toward their adoption. In the context of AI pricing, the perceived typicality of AI pricing plays a pivotal role in shaping fairness perceptions concerning the impact of dynamic pricing. Given the prevalence of personalized dynamic pricing over unified dynamic pricing in the implementation of AI pricing (Seele et al., 2021), coupled with the observation that consumers who are more acquainted with AI pricing tend to exhibit greater acceptance of personalized dynamic pricing, we propose a moderated moderation model. This model aims to predict a significant three-way interaction effect involving the perceived typicality of AI pricing, AI disclosure, and pricing type. Specifically, we posit that for consumers with a high perceived typicality of AI pricing, AI disclosure would mitigate the negative effects associated with personalized dynamic pricing. In contrast, for consumers with low perceived typicality of AI pricing, AI disclosure would exacerbate the adverse impact of personalized dynamic pricing.

From an attribution theory perspective, consumers with varying levels of perceived typicality of AI pricing engage in different attribution processes when AI is disclosed. Consumers with high perceived typicality of AI pricing are well-acquainted with AI pricing and tend to attribute personalized dynamic pricing more to AI. They believe that AI lacks subjective intentions and motivations and does not exhibit self-interested or irrational behaviors on its own accord. Consequently, they do not view personalized dynamic pricing as a tool employed by companies solely for profit-seeking purposes. Moreover, as algorithms adhere to consistent and predetermined procedures unaffected by human emotional factors, they entail fewer decision biases compared to human decision-makers (Schildt, 2017). The disclosure of AI further enhances these consumers' subjective perceptions of information transparency and the objectivity of the pricing mechanism. They perceive personalized dynamic pricing as objectively formulated by AI based on diverse information, resulting in a relatively high sense of price fairness.

Conversely, consumers with low perceived typicality of AI pricing lack familiarity with AI pricing and attribute personalized dynamic pricing more to the company itself (Chung & Petrick, 2013). They view AI disclosure as a protective measure employed by companies to mask their deliberate profit-maximization motives. They disagree with the notion that personalized dynamic pricing is an AI behavior devoid of subjective intentions and self-awareness. When AI disclosures are made, these consumers tend to ascribe stronger internal attributions to firms, which subsequently leads to lower perceptions of price fairness.

Therefore, we put forward the following hypothesis:

H3: The moderating effect of AI disclosure in the relationship between pricing type and fairness perceptions is moderated by the perceived typicality of AI pricing. For individuals with higher perceived typicality of AI pricing, AI disclosure will alleviate the negative effect of personalized dynamic pricing, while for individuals with lower perceived typicality of AI pricing, AI disclosure will intensify the negative effect of personalized dynamic pricing.

Figure 1 shows our hypotheses and research model.

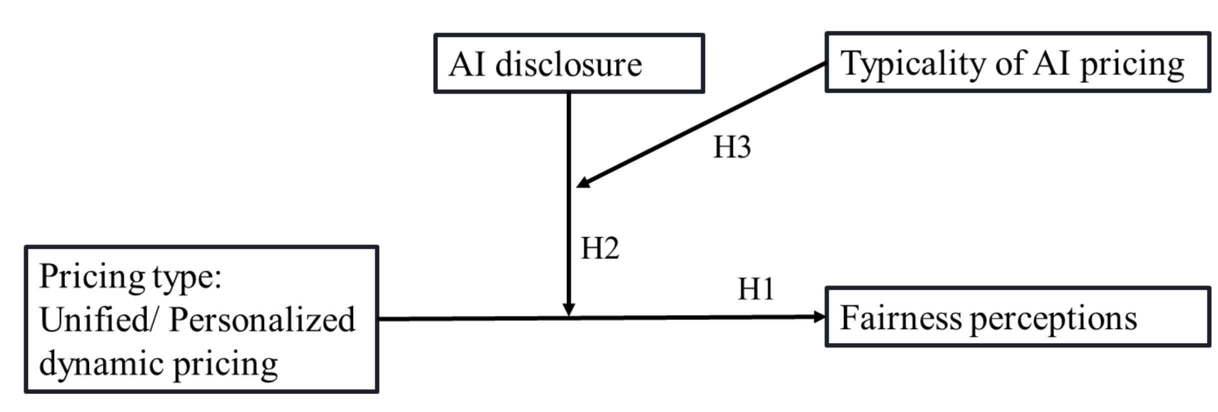

Figure 1. Research Model

Research Method

To examine the proposed hypotheses, a scenario-based experiment was conducted utilizing a 2 (pricing type: personalized vs. unified dynamic pricing) × 2 (AI disclosure: with vs. without) between-subjects design. Participants were presented with a scenario and instructed to imagine themselves within the described context (Wang et al., 2022). Subsequently, questionnaire data were collected to assess participants' perceptions and reactions toward dynamic pricing and AI disclosure.

Participants and Procedures

The study recruited students from various disciplines and levels at a Chinese public university through an online forum that served multiple purposes, including participant recruitment, and reached a large proportion of the student body. Only participants who passed the attention check were included in the analysis. Each participant received 5 RMB upon completing the experiment. In total, 145 participants (47% male) completed the survey and passed the attention check. Although most of the participants are students with an average age of 22, 81% of them have experience buying air tickets, and 95% of them have a monthly consumption amount of more than 1000 RMB. As such, the participants we recruited are appropriate for the experiment situation of buying air tickets. Participants are randomly assigned to one experiment condition, and no significant demographic difference exists among the groups.

In our study, stimuli materials are designed based on the interface of booking airline tickets. The materials have real airline information and appropriate price. All the groups set the scenario of price increasing a week later. To manipulate the price type, participants are provided with a friend's airline ticket price in the later week. In the condition of personalized dynamic pricing, the participant's price is 839 RMB, 100 RMB higher than his friend's. In the condition of unified dynamic pricing, the participant's price is the same as his friend's. These settings are in line with the real scenario that air tickets become more expensive over time, and the price increase and price difference with others are also in line with reality. To manipulate AI disclosure, only participants in the condition of AI disclosure will see a note "The following price is set by artificial intelligence." in each booking interface. Figure 2 shows the stimuli materials in the condition of personalized pricing with AI disclosure. In the beginning, we randomly assigned participants to one of four conditions. Participants were instructed to imagine that they had intended to buy a 639 RMB air ticket for a trip (see Figure 2a). A week later, they discovered that their ticket price had risen by 200 RMB to 839 RMB (see Figure 2b), while their friend's ticket price was either lower or equal to theirs. Participants in the personalized dynamic pricing group saw that their friend's ticket price was 739 RMB, which was 100 RMB cheaper than theirs (see Figure 2c). Participants in the unified dynamic pricing group saw that their friend's ticket price was 839 RMB, which was equal to theirs. Before participants responded to the questionnaire, we asked questions about price changes to make sure they had read stimulate material carefully. The front part of the questionnaire is to investigate their reactions in this scenario, and the back part is their personal information (i.e., age, gender, job), monthly consumption amount, the experience of buying air tickets, as well as their perceived typicality of AI pricing.

Figure 2a. Initial price **Figure 2b. Price a week later** **Figure 2c. Friend's price a week later**

Figure 2. Stimuli Materials in the Condition of Personalized Pricing with AI Disclosure

Measures

In dynamic pricing scenarios, consumers' perceptions of fairness often rely on two dimensions: procedural fairness (pertaining to the fairness of the decision-making process) (Bos et al., 1997) and distributive fairness (concerning fairness in the allocation of resources or benefits) (Ferguson et al., 2014). To assess consumers' perceptions of price fairness under different conditions of pricing type and AI disclosure, we utilized established measurement scales. The measurement items for procedural fairness and distributive fairness were adopted from the work of Chung and Petrick (2015). Additionally, three items were adapted to measure the perceived typicality of AI in dynamic pricing based on Campbell's (2007) measurement scale. All measurement items were rated on a 9-point Likert scale, ranging from 1 ("strongly disagree") to 9 ("strongly agree"). Table 1 provides an overview of the measurement items for the latent variables. To ensure the content validity of our measurements, the original scale was translated and revised by professors and Ph.D. students specializing in English and management.

Construct	Items	Factor loading	CR	AVE	CA
Procedural fairness	PF1: The airline's pricing decision processes and procedures were reasonable.	0.820	0.841	0.639	0.880
	PF2: The airline's pricing decision processes and procedures were fair.	0.850			
	PF3: The airline's pricing decision processes and procedures were acceptable.	0.722			
Distributive fairness	DF1: The price changes in air tickets were fair.	0.767	0.820	0.603	0.878
	DF2: The price changes in air tickets were acceptable.	0.768			
	DF3: The price changes in air tickets were clearly understandable.	0.794			
Perceived typicality of AI pricing	TY1: In everyday life, many companies use artificial intelligence for dynamic pricing.	0.944	0.964	0.898	0.945
	TY2: From what I understand, the use of artificial intelligence for dynamic pricing is quite usual.	0.955			
	TY3: I think it is typical for companies to use artificial intelligence for dynamic pricing.	0.944			

Table 1. Assessments of the Measurement Model

Results

Test of the Measurement Model

The measurement model was verified through a factor analysis as a preliminary step. The results indicated that the cumulative variance accounted for by all factors was 82.919%. The Kaiser-Meyer-Olkin (KMO) value, which measures the degree of correlation between variables and suitability for factor analysis, was found to be 0.845, suggesting a strong correlation among the variables and the appropriateness of conducting factor analysis. Additionally, Bartlett's sphericity test yielded a significant result ($p < 0.001$), indicating that there is a correlation among the variables and factor analysis is appropriate for the data.

To further assess the measurement model, two criteria were evaluated: construct reliability and construct validity (Hair et al., 2019). Construct reliability was evaluated using two measures: Cronbach's alpha (CA) and composite reliability (CR). The CA and CR values for each construct, as presented in Table 1, exceeded the threshold of 0.8, indicating an adequate level of reliability for the measurement items.

	Mean	SD	1	2	3
1. Procedural fairness	4.175	1.942	0.799		
2. Distributive fairness	4.594	1.646	0.712**	0.776	
3. Typicality of AI pricing	6.549	1.619	0.113	0.214**	0.948

Table 2. Pearson Correlation Coefficient and the Square Root of AVE

Notes: **$p < 0.01$; SD = standard deviation.

Convergent validity and discriminant validity were assessed to examine the measurement model further. Convergent validity is satisfied when all items measuring the same construct exhibit strong correlations. As depicted in Table 1, the factor loadings of all items exceeded 0.7, indicating a high level of correlation with their respective constructs. Additionally, the average variance extracted (AVE) for each construct exceeded 0.5, indicating that more than 50% of the variance in the indicators was explained by their respective constructs. These findings confirm the presence of convergent validity in the measurement model.

Discriminant validity evaluates the distinctiveness of different constructs. To assess discriminant validity, we compared the square root of the AVE values with the Pearson correlation coefficients between constructs (Fornell & Larcker, 1981). As shown in Table 2, the square root of the AVE for each construct is greater than the correlation coefficients between that construct and other constructs. This indicates that the measurement model demonstrates good discriminant validity, as the constructs are sufficiently distinct from one another.

Hypothesis Testing

To balance the sample numbers of each group, participants with perceived typicality of AI pricing lower than the median seven were divided into the low typicality group (N = 72), and others were divided into the high typicality group (N = 73). Table 3 shows the sample size of each group.

Group		Unified dynamic pricing	Personalized dynamic pricing
Low typicality	Without AI disclosure	18	17
	With AI disclosure	16	21
High typicality	Without AI disclosure	19	20
	With AI disclosure	20	14

Table 3. Sample Size of Each Group

We conducted a 2 (pricing type: personalized vs. unified dynamic pricing) × 2 (AI disclosure: with vs. without) × 2 (typicality of AI pricing: high vs. low) MANOVA to test our hypotheses (Hair et al., 2013). We also used SPSS (v. 22) software and PROCESS macro (v. 3.3), written by Andrew F. Hayes, to conduct a multiple regression analysis (Hayes, 2013). The results of multiple regression analysis are presented in Table 4 (Pricing type: 0=unified dynamic pricing, 1 = personalized dynamic pricing; AI disclosure: 0= without, 1 = with; Typicality of AI: 0 = low, 1 = high). All the results show that the main effect of pricing type and three-way pricing type× AI disclosure × typicality of AI pricing interaction is significant.

	Model 1		Model 2		Model 3	
Variable	Procedural fairness	Distributive fairness	Procedural fairness	Distributive fairness	Procedural fairness	Distributive fairness
Pricing type (0 = unified, 1 = personalized)	-2.186*** (0.188)	-1.727*** (0.233)	-2.126*** (0.376)	-1.476*** (0.327)	-1.575*** (0.530)	-1.339*** (0.463)
AI disclosure (0 = without, 1 = with)			0.236 (0.378)	0.336 (0.330)	1.403** (0.539)	0.954** (.470)
Typicality of AI (0 = low, 1 = high)					1.146** (0.516)	0.883* (0.450)
Pricing type x AI disclosure			-0.120 (0.537)	-0.512 (0.468)	-1.685** (0.743)	-1.286** (0.649)
Pricing type x Typicality of AI					-1.077 (0.730)	-0.297 (0.638)
AI disclosure x Typicality of AI					-2.188*** (0.736)	-1.180* (0.643)
Pricing type x AI disclosure x Typicality of AI					3.206*** (1.050)	1.775* (0.917)
R square	0.319	0.277	0.321	0.284	0.380	0.342
F change	67.019	54.803	22.262	18.621	11.991	10.187
Sig. F change	0.000	0.000	0.000	0.000	0.000	0.000

Table 4. Results of Multiple Regression Analysis

Notes: *p < 0.1, **p < 0.05, ***p < 0.01; all coefficients are standardized.

The results support hypothesis H1. MANOVA results show that the pricing type has a significant effect on participants' procedural fairness perception ($F(1, 137) = 67.379$, $p < 0.001$) and distributive fairness perception ($F(1, 137) = 54.186$, $p < 0.001$). Regression results in Table 4 Model 1 show a significant negative coefficient of pricing type (0 = unified, 1 = personalized) on procedural fairness perception ($\beta = -2.186$, $p < 0.001$) and distributive fairness perception ($\beta = -1.727$, $p < 0.001$). Participants have lower procedural fairness perception ($Mean_{\_Personalized} = 3.129$, $Mean_{\_Unified} = 5.283$) and lower distributive fairness perception ($Mean_{\_Personalized} = 3.770$, $Mean_{\_Unified} = 5.457$) when encountering personalized dynamic pricing than unified dynamic pricing.

Hypothesis H2 is not supported. MANOVA results show that the main effect of AI disclosure is insignificant on procedural fairness perception ($F(1, 137) = 1.041$, $p > 0.1$) and distributive fairness perception ($F(1, 137) = 0.517$, $p > 0.1$). The interaction effect of AI disclosure and pricing type is also insignificant on procedural fairness perception ($F(1, 137) = 0.024$, $p > 0.1$) and distributive fairness perception ($F(1, 137) = 0.757$, $p > 0.1$). Regression results in Table 4 Model 2 show an insignificant coefficient of AI disclosure and an insignificant coefficient of the interaction term of AI disclosure and pricing type.

More importantly, our hypothesis H3 is supported. MANOVA results show a significant three-way interaction among pricing type, AI disclosure, and perceived typicality of AI pricing interaction on procedural fairness perception ($F(1, 137) = 9.323$, $p < 0.01$, see Figure 3) and distributive fairness perception ($F(1, 137) = 3.750$, $p < 0.1$, see Figure 4). Regression results in Table 4 Model 3 show a significant positive coefficient of three-way interaction on procedural fairness perception ($\beta = 3.206$, $p < 0.01$) and distributive fairness perception ($\beta = 1.775$, $p < 0.1$). These results indicate that the interaction effect of price type and AI disclosure is moderated by consumers' perceived typicality of AI pricing. Specifically, AI disclosure mitigates the negative effect of personalized dynamic pricing relative to unified dynamic pricing for consumers with high perceived typicality of AI pricing while intensifying this negative effect for consumers with low perceived typicality of AI pricing. These results indicate that hypothesis H2 is not supported, which may be explained by the moderated moderation effect of perceived typicality of AI pricing on the effect of AI disclosure on the link between AI pricing type and fairness perceptions.

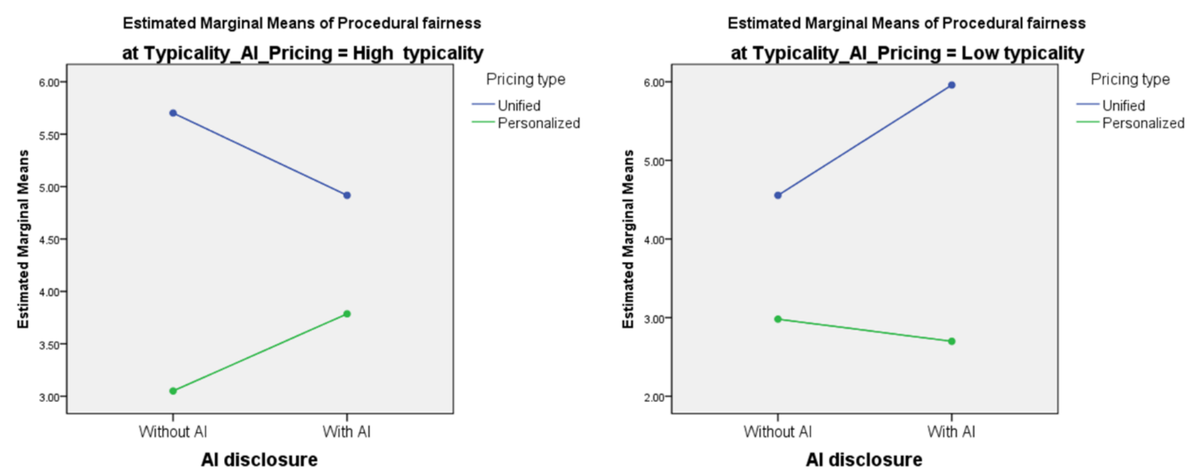

Figure 3. Results of Three-way Interaction Effect on Procedural Fairness

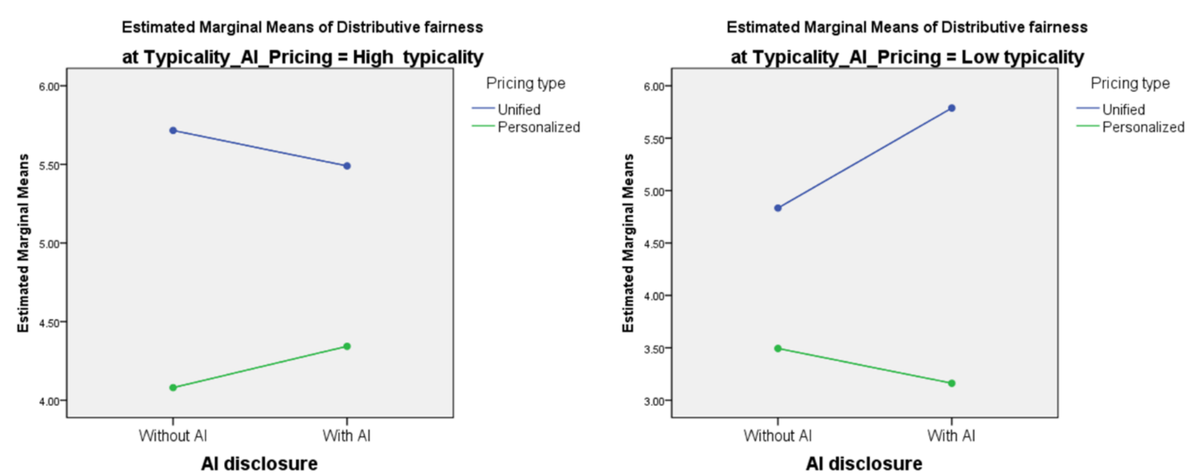

Figure 4. Results of Three-way Interaction Effect on Distributive Fairness

Next, we analyzed the two-way interaction effects of pricing type × AI disclosure among consumers with high or low perceived typicality of AI pricing, respectively. For participants with high perceived typicality of AI pricing, two-way pricing type × AI disclosure interaction is significant on procedural fairness ($F(1, 68) = 4.230$, $p < 0.05$) but insignificant on distributive fairness perception ($F(1, 68) = 0.574$, $p > 0.1$). Results show that the negative effect of personalized dynamic pricing is weaker when with AI disclosure than without AI disclosure on procedural fairness ($Mean_{(Personalized\text{-}Unified)\_WithAI} = -1.131$, $Mean_{(Personalized\text{-}Unified)\_WithoutAI} = -2.652$).

For participants with low perceived typicality of AI pricing, two-way pricing type × AI disclosure interaction is significant on procedural fairness ($F (1, 68) = 5.109$, $p < 0.05$) and distributive fairness perception ($F (1, 68) = 3.903$, $p < 0.1$). Results show that the negative effect of personalized dynamic pricing is stronger when with AI disclosure than without AI disclosure on procedural fairness ($Mean_{(Personalized\text{-}Unified)\_WithAI} = -3.260$, $Mean_{(Personalized\text{-}Unified)\_WithoutAI} = -1.576$) and distributive fairness perception ($Mean_{(Personalized\text{-}Unified)\_WithAI} = -2.618$, $Mean_{(Personalized\text{-}Unified)\_WithoutAI} = -1.339$).

Additionally, in the condition of personalized dynamic pricing with AI disclosure, consumers with low typicality perceived lower procedural fairness (difference = -1.087, $p < 0.1$) and lower distributive fairness (difference = -1.181, $p < 0.05$) than consumers with high perceived typicality of AI pricing.

The above interact effects supported hypothesis H3. Results indicate that AI disclosure can alleviate the negative effect of personalized dynamic pricing relative to unified dynamic pricing for consumers with high perceived typicality of AI pricing. However, for consumers with low perceived typicality of AI pricing, AI disclosure will intensify the negative effect of personalized dynamic pricing.

Robustness Check

In the previous analysis, we divided participants into different groups according to the median of perceived typicality of AI pricing. Participants lower than the median 7 were divided into the low typicality group and others into the high typicality group. However, some participants' perceived typicality of AI pricing is right 7. So, we divided participants higher than the median 7 into the high typicality group, and others were divided into the low typicality group. Results still show a significant three-way interaction effect among pricing type, AI disclosure, and typicality of AI pricing on procedural fairness perception ($F (1, 137) = 14.188$, $p < 0.001$), and distributive fairness perception ($F (1, 137) = 5.917$, $p < 0.05$). When we divided participants according to the mean 6.62 of perceived typicality of AI pricing, the three-way interaction effect is also significant on procedural fairness perception ($F (1, 137) = 7.847$, $p < 0.01$) and distributive fairness perception ($F (1, 137) = 4.329$, $p < 0.05$).

In our multiple regression analysis, we used PROCESS model 3 to test the moderated moderation model of AI disclosure and the typicality of AI pricing. After we replace the independent variable of perceived typicality from a categorical variable to a continuous variable, the three-way interaction still has a significant positive coefficient on procedural fairness perception ($\beta = 1.102$, $p < 0.001$) and distributive fairness perception ($\beta = 1.013$, $p < 0.001$). These results indicate that AI disclosure can alleviate the negative effect of personalized dynamic pricing relative to unified dynamic pricing for consumers with high perceived typicality of AI pricing. These robust results support our hypotheses H1 and H3 again.

Discussion

Contribution

Our research study has made several significant contributions. First, the present study has made contributions by enhancing the existing literature on price fairness, specifically in addressing the negative impact associated with personalized dynamic pricing. Prior research in the field of price equity has identified various moderating factors, such as consumer's individualistic cultural characteristics, other consumers' efforts, the enterprise's price framework, and bundling sales, as influencing the perception of price fairness in relation to the interpersonal price gap (Lastner et al., 2019; Li et al., 2018). Within the broader framework of attribution theory, our study uncovers the crucial role of AI disclosure as an additional factor in mitigating the adverse consequences associated with personalized dynamic pricing for specific consumer segments. Moreover, we identify the perceived typicality of AI pricing as a boundary condition for the impact of AI disclosure and demonstrate the moderating effect of AI disclosure and pricing types based on varying levels of perceived typicality of AI pricing. By shedding light on these aspects, our study contributes to a more systematic understanding of the underlying mechanisms governing consumer perceptions of price fairness within the context of AI pricing. Furthermore, our research expands and enriches the existing body of knowledge on the perception of price fairness in the era of artificial intelligence, particularly in the context of dynamic pricing.

Second, this study extends the existing literature on algorithmic decision-making by investigating the impact of AI in the context of dynamic pricing. Prior research has highlighted the phenomenon of algorithmic aversion among consumers when choosing between algorithmic decision-makers and human decision-makers. For instance, consumers have shown reluctance to rely on algorithms to predict stock prices (Önkal et al., 2009), seek medical advice (Cadario et al., 2021; Longoni et al., 2019), and make judgments about individuals' performance (Dietvorst et al., 2015). Building upon this literature, our research provides empirical evidence of how AI influences consumers' fairness perceptions in the realm of dynamic pricing. Furthermore, our findings demonstrate that consumers exhibit both algorithmic aversion and preference in the context of dynamic pricing, depending on specific situational factors. This extends our understanding of consumers' attitudes and responses toward algorithmic decision-making, shedding light on the nuanced relationship between AI and consumer perceptions in dynamic pricing scenarios.

In addition to the aforementioned contributions, this study contributes to a better understanding of the diverse psychological cognitions and behavioral responses exhibited by different consumers when encountering AI. Previous research has indicated that consumers hold distinct beliefs regarding the advantages and disadvantages of algorithms compared to human decision-makers. Algorithms are often perceived as more objective (Lee, 2018) but also as less realistic, less intuitive, and potentially more morally questionable (Bigman et al., 2023; Jago, 2019; Yeomans et al., 2019). Prior studies have primarily focused on investigating algorithmic aversion, which can vary based on situational factors such as the nature of the task (subjective and objective) (Castelo et al., 2019) and the enjoyment and utility derived from a product (Longoni & Cian, 2022). In contrast, this study demonstrates that algorithmic aversion is also influenced by consumer heterogeneity, specifically the perceived typicality of AI pricing. Notably, consumers with higher perceived typicality of AI pricing exhibit greater acceptance of personalized dynamic pricing and subsequently hold higher perceptions of fairness following AI disclosure. By exploring the moderating effect of perceived typicality of AI pricing, our research contributes to a deeper understanding of how consumer attitudes towards algorithms can vary based on individual differences, thereby advancing our knowledge of the intricate interplay between AI, consumer perceptions, and behavioral responses.

Managerial Implications

Utilizing algorithms for dynamic pricing presents significant potential for sellers. However, practitioners must contend with customers' negative reactions to personalized dynamic pricing, which can offset the potential monetary benefits. Previous studies have highlighted that consumers' acceptance of prices is contingent upon their perceptions of fairness (Zhang et al., 2022). Unfair price settings can engender negative attitudes and behavioral responses among consumers. The underlying premise for such negative attitudes and reactions is the ability of customers to compare prices, enabling them to discern interpersonal differences. With the proliferation of price comparison portals, social media platforms, and price search tools, consumers can easily identify personalized dynamic pricing online (Richards et al., 2016). Consequently, online sellers need to exercise caution when implementing algorithmic pricing, as it can disrupt the consensus on fair pricing strategies and related social norms (Maxwell & Garbarino, 2010).

Our research demonstrates that AI disclosure positively influences fairness perceptions among consumers who perceive AI pricing as typical. Consistent with Kuo, Rice, and Fennell (2016), becoming more familiar with dynamic pricing practices is conducive to perceiving price fairness. In the future, as algorithmic pricing becomes more prevalent across various industries, it is likely to gain wider recognition. Managers can consider enhancing consumers' perceived typicality of AI pricing and implementing AI disclosure to mitigate the negative impact of personalized dynamic pricing. We recommend that pricing strategists incorporate customers' perceived typicality of AI pricing into their simulation models when assessing the impact of price changes on revenue. Furthermore, the design of pricing display interfaces should consider user characteristics and whether AI pricing disclosure should be employed.

It is important to acknowledge that people's attitudes toward algorithmic pricing can vary significantly across different industries. This variability should be taken into account when evaluating consumers' fairness perceptions. Personalized dynamic pricing in industries such as hotels or airlines tends to be more acceptable due to the inherent dissimilarity of their services, distinctive characteristics, and additional benefits offered. Therefore, the implementation of personalized dynamic pricing is best accompanied by product or service customization, as this enhances the uniqueness and may divert attention from price differences (Weisstein et al., 2013).

Limitations and Future Research

The present study should be interpreted in light of several limitations, which offer opportunities for future research. While scenario-based experiments offer strong internal validity, their external validity may be limited (Wang et al., 2022). Due to practical constraints, the majority of our sample consisted of students, and we relied on self-reported behavioral intentions in the stimulus materials. Future research could employ observational methods in a more realistic setting to enhance the generalizability of the findings.

Furthermore, the experiment conducted in this study focused on the price increment of air tickets on a single route provided by an airline. However, the impact of personalized dynamic pricing on consumer behavior may vary depending on the product or service categories, the industry context, or the relative advantages derived from price discrimination (Hufnagel et al., 2022). Future research could explore personalized dynamic pricing of alternative product categories that do not have pre-existing consumer expectations of price fluctuations over time or in other industries or examine cases involving competition among multiple commodities or situations where consumers benefit from price discrimination.

Although this paper investigates the influence of AI disclosure and the perceived typicality of AI pricing on fairness perceptions of dynamic pricing, it does not delve deeply into the underlying mechanisms and consequences of changes in consumer fairness perceptions. Future research can expand on this by examining the specific mechanisms and exploring the broader implications of changes in fairness perceptions. Additionally, previous studies have suggested that the framing of AI pricing disclosure can indirectly affect purchase intention through the perception that the use of behavioral pricing information is driven by self-interest (Boom et al., 2020). Future research could investigate how different framing strategies of AI pricing disclosure influence consumers' purchase intentions.

Future research can also explore alternative methods for mitigating the negative impact of personalized dynamic pricing. Previous studies have shown that consumers' comprehension of the information collected can have a negative effect on their concerns (Niemann & Schwaiger, 2016). Therefore, managers could enhance the sense of price fairness and information transparency by informing customers about the information collected and how it will be utilized.

In summary, while this study makes significant contributions, it is essential to acknowledge its limitations and recognize the potential avenues for future research to address these limitations and further advance our understanding of algorithmic pricing and its implications.

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