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Algorithmic Price Discrimination and Negative Word-of-Mouth: The Chain Mediating Role of Deliberate attribution and Negative Emotion

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[Abstract]

This study aims to explore the impact of algorithmic price discrimination on negative word-of-mouth (NWOM) through the lens of attribution theory. It also examines the mediating roles of intentional attributions and negative emotions, as well as the moderating effect of price sensitivity. For this study, 772 consumers who had purchased flight tickets completed a questionnaire survey, and the collected data were analyzed and tested using SPSS 27.0 and AMOS 24.0 software. The research findings reveal that algorithmic price discrimination has a significant positive impact on intentional attributions, negative emotions, and NWOM. Specifically, deliberate attributions and negative emotions mediate the relationship between algorithmic price discrimination and NWOM, while price sensitivity positively moderates the relationship between negative emotions and NWOM. Therefore, companies should consider disclosing algorithm details transparently in their marketing strategies to mitigate consumers' negative emotions and implement targeted strategies for consumers with different levels of price sensitivity to enhance positive word-of-mouth.

▸ **Key words**: Big data algorithms, Price discrimination, Deliberate attribution, Negative emotion, Negative word-of-mouth

[요 약]

본 연구는 알고리즘 기반 가격차별이 부정적 입소문(NWOM)에 미치는 영향을 규명하는 것을 목표로 하며 귀인 이론을 통해 살펴본다. 또한, 고의귀속과 부정적 감정의 매개 효과과 가격 민감도의 조절 효과도 검토한다. 이를 위해 772명의 항공권을 구매한 소비자들이 설문 조사를 완료하였고, 수집된 자료는 SPSS 27.0 및 AMOS 24.0 소프트웨어를 이용하여 분석 및 검증되었다. 연구 결과는 알고리즘 기반 가격차별이 고의귀속, 부정적 감정 및 NWOM에 유의한 긍정적 영향을 미치는 것을 보여준다. 특히, 고의귀속와 부정적 감정이 알고리즘 기반 가격차별과 NWOM 간의 관계를 매개하고, 가격 민감도는 부정적 감정과 NWOM 간의 관계를 긍정적으로 조절한다. 따라서 기업들은 소비자들의 부정적인 감정을 완화하고 긍정적 입소문을 강화하기 위해 마케팅 전략에서 알고리즘의 세부 내용을 투명하게 공개하는 것을 고려해야 하며, 가격 민감도에 따라 대상 소비자들에게 맞춤형 전략을 시행해야 한다.

▸ **주제어**: 빅데이터 알고리즘, 가격차별, 고의귀속, 부정적 감정, 부정적 입소문

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I. Introduction

With the rapid development of information technology, numerous internet-based consumer platforms have emerged. These platforms, characterized by extensive product (or service) coverage, low transaction costs, and ease of operation, have garnered significant attention from users. They employ algorithms to analyze consumer behavior data, gaining deep insights into consumer interests and preferences, thereby enabling personalized recommendations and enhancing consumer loyalty and transaction volume[1].

However, it's important to note that while traditional price discrimination refers to companies applying different pricing strategies for consumers based on their characteristics, such as age, gender, and geographic location, algorithmic price discrimination is distinct. It leverages machine learning and Big Data analysis technologies to accurately segment customers based on their attributes and implement differentiated pricing strategies, often more covert[2]. Algorithmic price discrimination is prevalent across various industries, including aviation, consumer goods, and entertainment ticketing[3]-[5]. Examples of algorithmic price discrimination include: Platforms applying differential pricing to similar products or services based on customer transaction records and search histories. Platforms charging different prices to new and existing customers for the same product on the same platform. Although advanced pricing algorithms enable companies to maximize revenue, consumers generally perceive this practice as unfair and tend to attribute it to deliberate actions by the companies[6]-[9]. Such perceptions may trigger negative emotions in consumers, such as anger and disappointment, leading to negative reactions, such as spreading negative word of mouth (NWOM) and changing consumer behavior. These reactions can significantly impact companies[10][11].

There are three types of price discrimination: ○ First-degree price discrimination: Companies set different prices for each individual consumer to capture their willingness to pay fully. ○ Second-degree price discrimination: Companies formulate different price strategies based on the quantity purchased or consumer behavior patterns. ○ Third-degree price discrimination: Companies set different prices based on the characteristics and demand elasticity of different markets or consumer segments. Moderate second and third-degree price discrimination can enhance social welfare and achieve win-win outcomes[12]. However, it is worthwhile to explore the impact of algorithmic price discrimination on consumer perception and behavior. This research is significant because it can help companies formulate reasonable pricing strategies, safeguard consumer rights, improve market efficiency, and promote sustainable development.

In conclusion, this paper focuses on consumers who have purchased flight tickets, constructing a factor relationship model that explains how algorithmic price discrimination influences word of mouth on internet ticket purchase platforms. Specifically, the study aims to: Investigate the direct impact of algorithmic price discrimination on NWOM. Explore consumer psychology by incorporating deliberate attribution and negative emotion into the research scope, examining their influence on word of mouth and their roles in the overall relationship. Identify whether consumers' responses to NWOM differ based on their price sensitivity. This research aims to expand the field of algorithmic price discrimination, enrich relevant theories, and provide theoretical support and practical guidance for marketing strategies on flight ticket purchase platforms. The following section will further review the relevant theoretical background, clarify the research hypotheses of this paper, and detail the research methods and data analysis. Finally, the study results will be presented, discussed, and concluded.

II. Literature Review and Hypotheses

1. Algorithmic Price Discrimination and Negative Word of Mouth

Algorithmic Price Discrimination and Negative Word of Mouth Discrimination can lead to dissatisfaction because it is a humiliating, unfair, and repulsive experience[13]. Vulnerable consumers express their dissatisfaction with discrimination in various ways, such as NWOM[14]. When consumers perceive algorithmic price discrimination, they may feel unfairly treated and believe that the company has pricing issues, leading to expressions of dissatisfaction and criticism through NWOM. This negative word of mouth is conveyed through verbal communication, social media, online reviews, and can negatively impact the company's reputation and brand image[15]. Therefore, the hypotheses are as follows:

H1: Algorithmic price discrimination significantly positively influences negative word of mouth.

2. Algorithmic Price Discrimination, Deliberate attribution, and Negative Word of Mouth

Algorithmic Price Discrimination, Deliberate Attribution, and Negative Word of Mouth Deliberate attribution refers to attributing a certain outcome to the intentional actions of an individual or organization[16][17]. Compared to unintentional harm, deliberate harm elicits stronger negative emotions from consumers, leading to more intense criticism and making it harder to obtain forgiveness, thereby having a greater impact on the evaluation of the main brand[18][19]. When the degree of algorithmic price discrimination is low, consumers tend to believe that the subjective intent and motive of the online platform are not as strong. They think that the online platform would not engage in irrational behavior of price discrimination for such small price differences, and they are more likely to attribute it to technical or market factors. When consumers attribute algorithmic price discrimination to the deliberate actions of the company, they are more likely to express dissatisfaction and negative evaluations, and form NWOM. Therefore, the hypotheses are as follows:

H2: Algorithmic price discrimination significantly positively influences deliberate attribution.

H3: Deliberate attribution significantly positively influences negative word of mouth.

H4: Deliberate attribution mediates the relationship between algorithmic price discrimination and negative word of mouth.

3. Algorithmic Price Discrimination, Negative Emotion, and Negative Word of Mouth

Algorithmic Price Discrimination, Negative Emotion, and Negative Word of Mouth Although there is no previous research on algorithmic pricing, existing studies indicate that price fluctuations can trigger hostility from customers[20][21]. According to [20]'s study, price increases not closely related to cost increases can anger consumers. Both positive and negative emotions have a significant impact on consumer attitudes and actual purchasing behavior[22]. Algorithmic price discrimination is considered a deliberate personalized pricing strategy adopted by companies, which may trigger negative emotions from consumers. Consumers may feel discriminated against or treated unjustly, increasing the likelihood of negative emotions. When consumers experience negative emotions, they are more likely to express dissatisfaction with the company and spread NWOM. Negative emotions stimulate consumer criticism and negative evaluations of the company. Therefore, the hypotheses are as follows:

H5: Algorithmic price discrimination significantly positively influences negative emotion.

H6: Negative emotion significantly positively influences negative word of mouth.

H7: Negative emotion mediates the relationship between algorithmic price discrimination and negative word of mouth.

4. The Moderating Role of Price Sensitivity

Price sensitivity refers to the degree to which individual consumers perceive and respond to price changes for products or services[23]-[25]. Algorithmic pricing can elicit responses from both buyers and sellers[26][27]. Consumers with higher price sensitivity are more sensitive to price changes in products or services, and they may pay more attention to the trade-off between price and product performance. When they encounter negative experiences or experience price discrimination during the purchasing process, they are more likely to link negative emotions with price factors, thereby increasing the likelihood of generating NWOM. Therefore, the hypotheses are as follows.

H8: Price sensitivity positively moderates the relationship between negative emotion and negative word of mouth.

5. Deliberate Attribution and Negative Emotion

As the intensity of algorithmic price discrimination increases, consumers may attribute it to the deliberate actions of the company, believing that the company deliberately adopts unfair pricing strategies. The perceived deliberated attribution triggers negative emotions in consumers[18][19], such as anger, disappointment, and dissatisfaction. Negative emotions further prompt consumers to express dissatisfaction and criticism of the company, transmitting negative experiences and discontent through word of mouth, thereby having a negative impact on the company's reputation and image. Therefore, the hypotheses are as follows.

H9: Deliberate attribution has a significant positive impact on negative emotion.

H10: DDeliberate attribution exhibits a chain-mediated effect between algorithmic price discrimination and negative word of mouth via negative emotion.

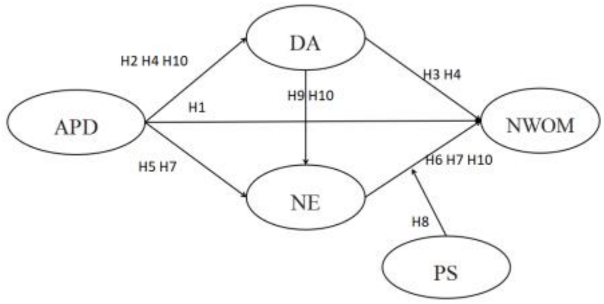

Fig. 1. Research Model

Note: APD(Algorithmic Price Discrimination); DA(Deliberate Attribution); NE(Negative Emotion); NWOM(Negative Word of Mouth); PS(Price Sensitivity);

III. Methodology

1. Sampling and Data Collection

To ensure the scales employed in this study possess a high level of reliability and validity, we referenced scales used by multiple scholars both domestically and internationally. Based on the specific research context, we formulated the initial version of the scales. Acknowledging the influence of cultural differences, we semantically revised the scales to align with the linguistic norms and cultural background of China, ultimately creating a set of viable scales.

This study targeted Chinese consumers as survey participants and utilized both online (survey questionnaire collection platform, email) and offline surveys. After excluding unqualified questionnaires, a total of 772 valid questionnaires were collected, resulting in an 89.8% valid questionnaire recovery rate. Among the participants, 55.2% were male and 44.8% were female. Regarding age distribution, individuals aged 26-44 accounted for 50% of the total. In terms of educational background, individuals with undergraduate degrees constituted the highest proportion at 43.5%. Regarding occupation, employees in enterprises had the highest representation, followed by civil servants and students. Lastly, survey participants with a monthly income ranging from 3001 to 5000 RMB accounted for 34.6%.

2. Measurement of Variables

In this study, each item was measured using a Likert 5-point scale. For each item, "1" indicated "completely disagree," and "5" indicated "completely agree." The following variables were measured using items adapted from previous studies: algorithmic price discrimination (3 items; Klinner & Walsh, 2013[28]), price sensitivity (3 items; Goldsmith et al., 2005[23]), deliberate attribution (4 items; Vaidyanathan & Aggarwal, 2003[29]), negative emotion (3 items; Westbrook & Oliver, 1991[30]), and negative word of mouth (3 items; Grégoire et al., 2010[31]).

IV. Data Analysis and Results

1. Reliability and Validity Analysis

Reliability and validity tests of variables were conducted using SPSS 27.0 and AMOS 24.0 software. All variables had Cronbach's α reliability coefficients greater than 0.7, indicating high questionnaire reliability. Additionally, all variables had Composite Reliability (CR) greater than 0.8, indicating good internal consistency of the questionnaire(Table 1).

Validity was tested using principal component factor analysis with maximum variance rotation. A total of 5 factors were extracted, consistent with this study's research. Bartlett's Test of Sphericity resulted in 0.000, and the KMO value was 0.843, with all factor loading values above 0.7, indicating good structural validity of the scale. Each variable had Average Variance Extracted (AVE) higher than 0.5, and the correlation coefficients between factors were smaller than the square root of AVE (Table 2), further demonstrating the great convergent and discriminant validity.

Table 1. Reliability and validity statistics

Construct	Code	Loadings	Cronbach's Alpha	AVE	CR
DA	DA1	0.809	0.826	0.626	0.870
	DA3	0.803			
	DA2	0.793			
	DA4	0.758			
APD	APD1	0.808	0.78	0.631	0.837
	APD3	0.8			
	APD2	0.774			
NWOM	NWOM3	0.815	0.787	0.641	0.842
	NWOM2	0.806			
	NWOM1	0.78			
NE	NE3	0.813	0.79	0.613	0.826
	NE1	0.787			
	NE2	0.748			
PS	PS1	0.816	0.738	0.647	0.84
	PS2	0.807			
	PS3	0.79			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.				0.843	
Bartlett's Test of Sphericity	Approx. Chi-Square			4206.421	
	df			120	
	Sig.			0.000	
Extraction Method: Principal Component Analysis.					
Rotation Method: Varimax with Kaiser Normalization.					
a Rotation converged in 6 iterations.					

According to the Fornell-Larcker criterion, each latent variable had a square root of AVE greater than its correlation with other variables[32], as shown in Table 2.

Table 2. Latent variable correlation and the square root of AVE

	APD	DA	NE	NWOM	PS
APD	0.883				
DA	0.228**	0.791			
NE	0.471**	0.361**	0.889		
NWOM	0.372**	0.332**	0.364**	0.887	
PS	0.081*	0.083*	0.181**	0.174**	0.859
Note: ***p<.001, **p<.01, *p<.05					
The values on the diagonal represent the square root of the AVE of each construct.					

2. Hypothesis Test

AMOS 24.0 was used to test the fit of the model to the data. The fit indices reflect the overall fit and acceptability of the model. After analyzing the characteristics of the fit indices, seven fit indices were selected to test the model (Table 3). All the fit indices exceeded the optimal standard suggested in

SEM literature, indicating that the observed model fitted the sample data very well.

Table 3. Comparison between Fitting Results and Ideal Results of Model and Data

The revised index	CMIN/DF	GFI	AGFI	CFI	NFI	TLI	RMSEA
Ideal results	<3,1<	>0.9	>0.9	>0.9	>0.9	>0.9	<0.05
The fitting results	1.345	0.984	0.975	0.994	0.978	0.992	0.021

Based on good model fit, path analysis was conducted to test the proposed hypotheses, using the path coefficients and significance between variables (Table 4). All the main effect paths were significant.

Table 4. Structural Equation-AMOS Model Path Analysis Results

	Estimate	S.E.	C.R.	P	Hypothesis	Conclusion
APD→NWOM	0.302	0.057	5.322	***	H1	Support
APD→DA	0.249	0.041	6.147	***	H2	Support
DA→NWOM	0.268	0.052	5.191	***	H3	Support
APD→NE	0.521	0.049	10.733	***	H5	Support
NE→NWOM	0.149	0.06	2.49	0.013*	H6	Support
DA→NE	0.343	0.048	7.12	***	H9	Support

3. Chain Mediating Effect Analysis

PROCESS (Hayes, 2018) with Bootstrap method was used to verify the chain mediation effect of deliberate attribution and negative emotion[33]. As shown in Table 5, the Bootstrap 95% confidence intervals for these three paths did not include 0, indicating that all three indirect effects were significant, confirming the acceptance of hypotheses H4, H7, and H10.

Table 5. Chain Mediating Effect Analysis

	Effect	Boot SE	Boot LLCI	Boot ULCI	Percentage of total effect
Total effect	0.382	0.034	0.315	0.45	100%
Direct effect	0.248	0.037	0.176	0.321	65%
Indirect effect	0.134	0.02	0.094	0.174	35%
APD→DA→NWOM	0.05	0.011	0.031	0.074	13%
APD→NE→NWOM	0.073	0.016	0.042	0.106	19%
APD→DA→NEE→NWOM	0.011	0.003	0.006	0.017	3%

4. Moderation Effect Analysis

On the basis of the mediation test, the moderated mediation model was examined. Following Hayes' suggestion, the bias-corrected percentile Bootstrap method was used for testing, and Model 87 in Process was employed to examine the moderated mediation model[34]. The results in Table 6 showed that the interaction between negative emotion and price sensitivity significantly predicted negative word of mouth, demonstrating that price sensitivity moderates the mediating effect between negative emotion and negative word of mouth ($\beta=-0.198$, $t=-5.204$, $p<0.001$), as shown in Table 3. Hence, the moderation effect was significant, confirming the acceptance of hypothesis H8.

To verify the moderated mediation effect, price sensitivity was divided into high (+1 SD) and low (-1 SD) groups. The differences between the high and low groups were tested to verify the moderated mediation effect. When price sensitivity was low, negative emotion had a significant mediating effect ($\beta=0.124$, 95% CI=[0.086, 0.166]); when price sensitivity was high, negative emotion had no significant mediating effect ($\beta=-0.008$, 95% CI=[-0.049, 0.033]). However, the difference between them was significant ($\beta=-0.066$, 95% CI=[-0.092, -0.041]), indicating that price sensitivity significantly moderated the mediating effect of negative emotion on negative word of mouth, as shown in Table 7.

Table 6. Moderation Effect Analysis

	Dependent Variable: NWOM		
	coeff	se	t
constant	-0.766	0.417	-1.836
APD	0.252	0.036	6.934***
DA	0.22	0.038	5.833***
NE	0.853	0.14	6.107***
PS	0.697	0.116	5.983***
NEExPS	-0.198	0.038	-5.204***
R-sq	0.262		
F	54.266		

Table 7. Moderated Mediation Effect Test

PS	Effect	BootSE	95%	
			BootLLCI	BootULCI
	APD-DA-NE-NWOM			
eff1(M-1SD)	0.124	0.021	0.086	0.166
eff2(M)	0.058	0.016	0.028	0.092
eff3(M+1SD)	-0.008	0.021	-0.049	0.033
eff2-eff1	-0.066	0.013	-0.092	-0.041
eff3-eff1	-0.132	0.026	-0.183	-0.082
eff3-eff2	-0.066	0.013	-0.092	-0.041

V. Conclusion and Discussion

1. Conclusion

This study constructed a factor relationship model that influences the online word of mouth on internet ticket purchasing platforms among consumers who have bought airline tickets. The results are as follows.

Algorithmic price discrimination has a positive impact on deliberate attribution, negative emotion, and negative word of mouth (NWOM), with the most significant effect on negative emotion (β=0.521). This may involve the use of personal information or consumer behavioral data for pricing, leading to consumers feeling a breach of their personal privacy, thereby amplifying negative emotions and enhancing their effects. Consumers on social media and online review platforms may encounter negative emotions from others, further exacerbating their own negative emotional states. In the confluence of these factors, algorithmic price discrimination has the most pronounced impact on negative emotions.

Algorithmic price discrimination, deliberate attribution, and negative emotions have a positive impact on negative word of mouth, with algorithmic price discrimination having the most significant influence (β=0.302). When consumers perceive pricing unfairness and discrimination, they often express their dissatisfaction and disappointment through negative word of mouth. Furthermore, deliberate attribution and negative emotions mediate the relationship between algorithmic price discrimination and negative word of mouth, further enhancing the expression and dissemination of negative word of mouth.

The relationship between price sensitivity and negative emotions is adjusted by negative reputation. Consumers with high price sensitivity tend to choose products based on a perspective of benefits (Fullerton & Taylor 2002). They may rationalize the shortcomings of some products in order to obtain cheaper prices. This rationalization behavior makes it less likely that negative emotions will be transformed into the spread of negative reputation.

2. Research Implications

This study uses mediation analysis to reveal the chain mediation process of deliberate attribution and negative emotion from algorithmic price discrimination to negative word of mouth. This helps to deepen the understanding of how consumers generate negative emotions when facing algorithmic price discrimination and express their dissatisfaction through word of mouth. It also provides new directions for the study of algorithmic price discrimination.

Specifically, the government should enact regulations concerning data privacy and security to mitigate consumers' concerns regarding the improper use of their personal information. Simultaneously, online platforms bear the responsibility of enhancing the transparency of pricing and pricing mechanisms. This includes providing detailed explanations of various factors influencing price determination, such as timing, demand, and seat location. Such improved transparency contributes to ensuring that price differentiation is built upon principles of fairness and equity, thereby safeguarding consumer privacy. This measure aids in reducing the potential negative impacts associated with breaches of personal privacy. Furthermore, airlines can contemplate adopting differential pricing strategies to mitigate the risk of price discrimination. This includes offering a wider range of price choices, subscription models, or loyalty programs to cater to the needs of consumers with varying price sensitivities.

Understanding consumers' levels of price sensitivity is crucial for internet ticket booking platforms. Price sensitivity can be distinguished based on historical transaction records, and differential strategies can be implemented. For consumers with high price sensitivity, personalized pricing and discount promotions are particularly vital. Special offers can be communicated through email or SMS notifications. Moreover, providing personalized recommendations to price-sensitive consumers can guide them to discover more affordable products or services. For consumers with low price sensitivity, a pricing tier approach proves effective. Creating multiple pricing tiers, each offering different prices and privileges, encourages price-sensitive consumers to upgrade to higher tiers for added benefits. This group often places greater emphasis on product quality and additional value. Therefore, companies can deliver higher levels of service, superior product quality, or other value additions to meet their needs. This can help attract and retain price-insensitive consumers, making them more willing to pay for a high-quality experience. In summary, these comprehensive strategies can assist businesses in better catering to consumers with varying price sensitivities, resulting in increased sales, reduced negative sentiments, and enhanced user satisfaction.

3. Research Limitations and Future Research

While this study provides a valid relationship path for academic research, there are also limitations and areas worthy of further exploration.

Firstly, this research exclusively surveyed Chinese consumers purchasing airline tickets, which may limit the generalizability of the research findings. To enhance generalizability, future studies may consider including consumers from diverse backgrounds and regions. Specifically, expanding the scope of the research to encompass consumers from different cultural backgrounds, socioeconomic levels, age groups, and professions can provide a more comprehensive understanding of consumer behaviors and preferences when purchasing airline tickets, thereby increasing the credibility and practicality of research findings. Moreover, employing various data collection methods, such as online surveys, face-to-face interviews, and observations, can capture specific consumer needs and behaviors more comprehensively and accurately. Additionally, integrating knowledge and theories from other related research areas can enhance the depth and breadth of the study. Drawing from theories and research findings in fields like marketing, consumer behavior, and psychology can better explain and analyze consumer ticket-purchasing behaviors and decision-making processes. In the realm of marketing, theories related to marketing strategies, brand positioning, and consumer demand analysis can shed light on consumer demand characteristics, brand preferences, and consumer psychology when it comes to purchasing airline tickets, leading to the development of more precise marketing strategies and better meeting consumer needs. In the realm of consumer behavior, theories related to consumer decision processes, purchasing behaviors, attitude formation, and the like can offer insights into consumer decision-making processes, influencing factors, and psychological mechanisms when purchasing airline tickets, ultimately improving our understanding of consumer behaviors and needs and providing robust support for airlines in devising more rational marketing strategies. Additionally, drawing from psychology theories such as cognitive psychology, social psychology, and behavioral psychology can provide in-depth insights into consumer psychological motivations, behavioral preferences, decision psychology, and other aspects, allowing for a better understanding of consumer psychological needs and behavioral characteristics. This understanding can, in turn, serve as a basis for airlines to provide more personalized services.

In conclusion, integrating knowledge and theories from other related research fields can augment the depth and breadth of the study, offering better explanations and analyses of consumer ticket-purchasing behaviors and decision-making processes. This, in turn, can provide robust support for airlines in formulating more reasonable and precise marketing strategies.

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