Journal of
Theoretical and Applied Electronic Commerce Research

MDPI

Article

"Buying Fewer but More Expensive": The Impact of Air Quality on Average Order Value (AOV) in Online Food Delivery and an Analysis of Consumer Behavior

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Abstract

While existing research has established that air pollution-induced "avoidance behavior" significantly drives the growth of online food delivery volumes, the Average Order Value (AOV) remains unexplored. This study utilizes micro-transactional data provided by the store owner and employs machine learning algorithms to detect the impact of air quality (measured by the AQI) on online food delivery AOV and analyze the underlying consumer behavior. The findings indicate that: (1) Air quality deterioration significantly drives up the AOV. The global average response coefficient is 0.0053, showing a 2.4-fold acceleration effect once the AQI crosses the median (66). (2) Crucially, this growth stems from a directional divergence in consumer decision-making. Air pollution leads to the simultaneous occurrence of a reduction in average item quantity (impact coefficient: −0.0014) and a surge in Average Item Price (AIP) (impact coefficient: 0.0066). (3) Causal analysis further identifies a "substitution mechanism." Specifically, every one-unit decrease in average item quantity induces a CNY 1.098 jump in average item price. These findings suggest a plausible behavioral logic where environmental stress may induce psychological fatigue but does not necessarily trigger "defensive frugality." Instead, the observed pattern is consistent with a "decision avoidance" mode where consumers streamline item quantities; simultaneously, to hedge against potential experience risks resulting from simplified choices, they appear to utilize saved cognitive resources to target high-value "signature" items. Theoretically, this study fills the gap in environmental stress research regarding the price dimension of online consumption and reveals a behavioral evolution from "pure avoidance" to "value-oriented selection." Practically, it provides empirical support for online food delivery merchants to optimize product selection, differentiate pricing, and implement precision marketing in dynamic environments.

Keywords: air quality; online food delivery; Average Order Value (AOV); consumer behavior; "buying fewer but more expensive"

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Academic Editors: Jolanta Kowal and Paweł Weichbroth

Received: 19 March 2026
Revised: 15 April 2026
Accepted: 15 April 2026
Published: 17 April 2026

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1. Introduction

"In the field of online on-demand delivery, the impact of environmental factors on consumer behavior has received extensive academic attention. Research by Chu et al. [1] has found that air pollution triggers "avoidance behavior," leading to a massive shift of dine-in demand toward online delivery channels. Subsequent studies [2] have also confirmed that food delivery order volumes increase under poor air quality. These studies

indicate that air pollution, as a significant external stressor, has become a key variable reshaping the landscape of the catering industry." These studies indicate that air pollution, as a significant external stressor, has become a key variable, reshaping the landscape of the catering industry. However, while existing literature has extensively demonstrated how environmental stress alters consumer channel choices and total order volumes, it has not yet explored the spending intensity of these orders—specifically, the Average Order Value (AOV).

This neglect of the "price" dimension leaves the direction of consumption decisions after the surge in "volume" as an unopened "black box." When environmental stress drives consumers toward online channels, whether the amount spent on a single food delivery order remains stable or undergoes structural reshaping is still lacking clear empirical evidence. Exploring this "black box" is not only of profound theoretical significance but also carries urgent practical management value. If air pollution merely changes the physical space of ordering without affecting the consumer's spending logic, merchants would only need to maintain their regular operational pace. However, if environmental stress reconstructs the consumer's bill structure, merchants must specifically adjust product weights, promotional strategies, and pricing logic. Before this "black box" is opened, merchants face risks of marketing misalignment or profit loss when attempting to capitalize on the traffic dividends resulting from environmental externalities.

To address this gap, this study utilizes first-hand transaction data from a "Mala Xiang Guo" (Spicy Hot Pot) delivery store provided by the owner to empirically examine the correlation between air quality and delivery AOV and to explore the underlying consumer behavior. The core task of this paper is to dissect delivery AOV to detect the possible impact of environmental stress on the consumer's delivery "bill structure." This exploration not only fills the gap in environmental risk research regarding the "spending intensity" dimension but also provides empirical support based on micro-trajectories for the precision operations of food delivery merchants in dynamic environments.

2. Literature Review

2.1. Air Quality Deterioration and the Expansion of Online Demand

"In the cross-disciplinary field of environmental risk and on-demand retail, a solid academic consensus has been established regarding the driving effect of air quality on the "total demand" for food delivery. Research in this dimension primarily comprises two levels: ordering frequency and total expenditure. First, studies on channel switching have confirmed traffic reshaping driven by air quality. Chu et al. [1] established a positive correlation between PM2.5 and the total volume of food delivery orders, explicitly identifying the cause as consumers' avoidance of air pollution. Research by Tian et al. [2] used massive transaction data to confirm that air pollution significantly triggers "avoidance behavior," leading to a massive shift of offline dine-in demand to online delivery channels, which explains the explosive growth in ordering frequency."

2.2. Theoretical Deduction from a Psychological Perspective: Conflict Between Defensive Frugality and Compensatory Consumption

Established research in the field of psychology regarding how psychological stress affects spending provides a theoretical reference for speculating on the internal structure of the AOV "black box." If poor air quality is viewed as an external factor that induces psychological burden or emotional stress, consumers' spending decisions will be driven by two opposing motives.

On one hand, environmental threats may induce "defensive frugality." The Conservation of Resources theory points out that when individuals are in a stressful environment, their primary motive is to protect existing resources to cope with future uncertain risks [3]. Sharma and Alter found that a sense of environmental threat can induce a feeling of financial scarcity, prompting consumers to become extremely pragmatic and cautious in their decision-making [4]. Durante and Laran confirmed through experiments that stress cues in the environment activate an individual's "survival goals," making them prone to discarding irrational premium consumption [5]. Under this logic, although consumers choose food delivery for avoidance purposes, the environmental threat may induce "defensive frugality." They might only choose low-priced basic meals or a smaller quantity of items to satisfy basic hunger, resulting in a declining trend in AOV despite the growth in order volume.

The second possibility is an increase in spending based on "compensatory psychology." Compensatory consumption theory suggests that when individuals are in a negative emotional state or feel a sense of deprivation, they seek emotional regulation or psychological repair through material acquisition [6,7]. Under this logic, consumption is viewed as a means of self-reward. In specific food delivery decisions, this may manifest as an impulse to "buy more expensive" or "buy more" to offset the displeasure caused by air quality deterioration. Consequently, consumers tend to choose higher-priced signature dishes, premium ingredients, or richer category combinations, exchanging this immediate material satisfaction for psychological comfort [8]. In other words, under poor air quality, consumers not only choose to order food delivery but also tend to order expensive food delivery (expensive delivery may result from "buying more items," "buying more expensive" items, or both). Research on consumer spending has also observed similar expansion trends. Kim and Trusov [9] utilized credit card big data to observe that a decline in air quality leads to a significant increase in consumers' total monthly expenditure, with a particularly marked expansion in hedonic consumption. This indicates that when air quality is poor, consumers may expand their spending on hedonism as a form of self-compensation.

There is a conflict between "defensive frugality" and "compensatory hedonism." Based on these theories, we are still unable to determine the impact of air quality on online food delivery AOV. Because if air quality is an external stressor, ordering food delivery could transition into either "defensive frugality" or "compensatory hedonism," and AOV could either rise or fall.

2.3. Multidimensional Context of Factors Influencing Online Consumption Decisions

With the proliferation of e-commerce and mobile internet technologies, academia has constructed a vast research matrix regarding "online decision-making inducements," aiming to deconstruct the behavioral logic of consumers in digital environments from various dimensions. First, the technology and system interaction dimension serves as the foundation of this field. Based on the Technology Acceptance Model (TAM) and its evolutionary theories, extensive literature has explored how perceived usefulness, ease of use, and interaction quality determine users' continuous usage intentions [10,11]. Second, the digital interface and atmospheric perception dimension has been studied in depth. Based on the Stimulus-Organism-Response (S-O-R) model, research has confirmed that atmospheric cues such as website navigation design, visual presentation, and information richness significantly influence consumers' emotional states, thereby inducing purchase impulses [12–14]. Additionally, the online trust and risk avoidance dimension is crucial to decision-making research. Scholars have extensively demonstrated how platform credibility, privacy protection, computational security, perceived risk, and initial trust facilitate ordering decisions by reducing uncertainty [15–19].

In the era of the mobile internet, the social interaction and algorithmic guidance dimension has become a new research hotspot. Electronic word-of-mouth (eWOM), social media interaction, community belonging, and online review quality have been proven to significantly alter individuals' purchase preferences and brand attachment [20–23]. Simultaneously, algorithm-driven personalized recommendations and information filtering mechanisms have accelerated the decision-making process and increased purchase frequency by significantly reducing consumers' search costs [24]. In the psychological motivation and individual characteristics dimension, scholars have distinguished the differentiated driving logic of hedonic and utilitarian motivations on decisions [25,26] and examined the reshaping effects of demographic variables such as age, gender, and shopping experience on decision inertia [27,28].

However, a comprehensive review of the aforementioned research contexts reveals that despite the abundance of empirical results regarding "why orders are placed" and "ordering frequency," a systemic blind spot exists: the long-term neglect of Average Order Value (AOV) as a value indicator. In the current empirical framework of e-commerce, the vast majority of studies tend to treat "purchase intention" or "purchase frequency" as the core dependent variables of the model, while viewing AOV merely as a descriptive variable that fluctuates with total volume. This paradigmatic bias has resulted in very little being known about "spending intensity per order" and its driving mechanisms, especially when an exogenous stressor such as air quality is involved.

2.4. The Impact of Temporal Factors and Weather on the Catering and Retail Industry

In addition to the aforementioned factors related to digital platforms and technology, existing literature on consumption decisions within the broader catering industry (without specifically distinguishing between online and offline channels) also emphasizes the significant role of temporal factors and the external environment. Temporal factors have been identified as crucial determinants of fluctuations in catering demand and spending intensity. Research indicates that the day of the week (workdays vs. weekends) and statutory holidays significantly reshape consumption frequency and order size by altering individuals' social motivations and leisure time costs; moreover, promotional activities during holidays have been shown to yield superior results (Wang et al., 2021) [29]. Weather also serves as a central cue driving catering decisions. Meteorological factors such as temperature, rainfall, and lighting influence human physiological comfort and emotional states, thereby impacting food product demand. For instance, Bujisic (2017) tested the effects of 17 different weather conditions on restaurant menu item demand, finding that specific weather factors have heterogeneous impacts across various menu categories [30]. Furthermore, studies investigating the non-catering retail sector, such as the research by Badorf and Hoberg (2020), demonstrate that weather has complex effects on daily store sales, with the magnitude and direction of the impact depending heavily on store location and sales themes [31].

2.5. Comparative Analysis of Online and Offline Consumption Decision Factors

Consumer decisions in catering exhibit both fundamental similarities and distinct differences between "offline dine-in" and "online food delivery" models. Regarding similarities, both models are governed by the same set of baseline temporal factors (e.g., weekends and statutory holidays) and meteorological conditions (e.g., temperature fluctuations and rainfall). However, while both channels are susceptible to weather conditions, these factors often produce diametrically opposite effects. Offline dining is typically "experience-oriented." Chua et al. (2020) [32] found that consumers choose to dine out primarily to seek environmental convenience, social interaction, and immediate sensory enjoyment within

the restaurant. In this context, rainfall or extreme temperatures are perceived as "barriers" because they increase the physical difficulty of traveling, which leads to a suboptimal dining experience [32]. In contrast, online food delivery is predominantly "convenience-oriented." Research by Cho et al. (2019) [33] demonstrates that convenience is the most critical driver for online ordering. In this scenario, rainfall or extreme temperatures act as "facilitators" because they increase the difficulty of offline travel, making food delivery the optimal choice for avoiding adverse environments and achieving effortless dining [33].

2.6. "Price" as the Research Gap

In summary, while existing literature has achieved substantial progress in the fields of environmental stress-driven consumption growth, multidimensional inducements for online decision-making, and general drivers for the catering and retail industries, a systematic comparison of the aforementioned research contexts (Sections 2.1–2.5) reveals a significant logical fracture and an empirical blind spot.

First, existing research has completed the logical loop from "environmental induce ments" to "demand scale" and "channel displacement," but it stops at the moment the transaction occurs. As discussed in Section 2.1, Section 2.4, and Section 2.5, academia has confirmed that air quality and meteorological factors can trigger "avoidance behavior," leading to a massive shift of traffic from offline to online channels. However, the core contribution of these studies lies in explaining "why consumers order delivery" and "how frequently they order" (the issue of *volume*), while ignoring the structural reshaping of spending intensity—measured by Average Order Value (AOV)—after consumers cross the digital threshold and enter the specific ordering phase (the issue of *price*). This neglect of the price dimension leaves the trajectory of AOV following a volume surge as an unopened "black box".

Second, existing analytical frameworks for online consumption decisions (Section 2.3) exhibit a pronounced "decision-heavy, spending-light" bias, leaving theoretical conflicts unresolved. Current e-commerce research explores in detail how interfaces, algorithms, and demographic characteristics facilitate the act of placing an order, yet few studies have established independent detection models for the spending structure of a single order. As shown by the psychological paradox in Section 2.2, when air quality deterioration is viewed as a psychological stressor, it could theoretically induce either "defensive saving," leading to a lower unit price, or "compensatory hedonism," driving a higher unit price. Without an empirical identification of the micro-value dimension of AOV, it remains unknown which psychological force dominates in the specific context of on-demand delivery.

Therefore, the research gap of this study is clearly manifested: When air quality deterioration (increasing environmental stress) drives an explosive growth in total online order volume, does the AOV shrink, expand, or remain neutral? How does the behavioral logic behind this variation evolve? By utilizing first-hand transaction-level data from a merchant's backend, this study aims to fill the vacuum in research regarding the price dimension of environmental stress-reshaped consumption. By deconstructing the price restructuring mechanism, this research provides micro-behavioral evidence for the product selection and pricing strategies of e-commerce delivery merchants in dynamic environments (Figure 1).

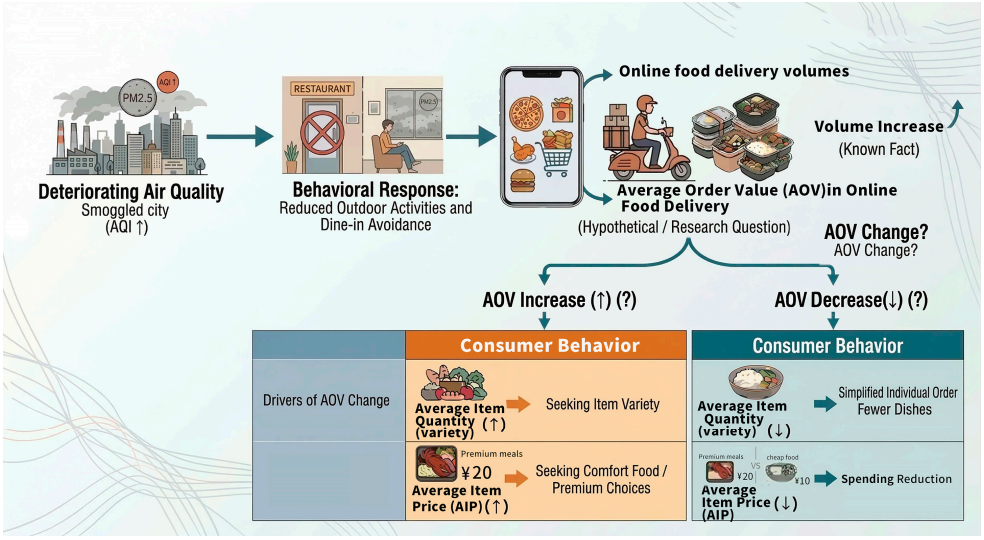


Figure 1. The Research Gap: Where Does the Average Order Value (AOV) Go Beyond the Surge in Volume?

3. Data and Methodology

3.1. Data Source and Sample Context

The empirical data for this study were provided by Mr. Junsong Huang, the owner and operator of a "Mala Xiang Guo" (Spicy Hot Pot) store located in Fuling District, Chongqing, China. Fuling is a key urbanized hub of Chongqing, characterized by high population density and a vibrant digital consumption market. It is important to note that this research is not a preliminary study but rather an exploratory empirical study based on authentic transaction trajectories.

(1) Economic Background and Natural Environment: In 2025, the per capita GDP of Fuling District was approximately 162,100 CNY, ranking among the highest in western Chinese cities and supporting a highly mature on-demand delivery infrastructure. The store's delivery radius covers a range of approximately 10 km, an area that encompasses multiple higher education institutions and office complexes, with a total population of around 150,000. Geographically, the region belongs to a subtropical monsoon climate. Although it never snows, the area is prone to smog during winter due to temperature inversions. Consequently, the Air Quality Index (AQI) exhibits a wide variance from autumn to winter, providing an ideal natural experimental field for investigating the impact of air quality on consumption behavior.

(2) Consumer Profile: According to user tag analysis from the store's backend, the core customer base primarily consists of young urban professionals and college students aged 18 to 40. This demographic is generally well-educated and exhibits a high degree of reliance on online food ordering platforms. In terms of purchasing power, this group possesses stable monthly disposable income and shows a consistent preference for catering formats like Mala Xiang Guo, which are characterized by "mid-to-high AOV" (compared to standard fast food). This ensures the sample's representativeness and sensitivity for analyzing spending restructuring.

(3) Sample Scale: The study selected operational data spanning from 28 October 2025 to 16 January 2026 (excluding non-operational dates, totaling 76 actual operating days). The sample includes every authentic transaction detail generated during this period, effectively excluding the human interference typically found in controlled laboratory environments.

3.2. Variable Description

The variable descriptions are shown in the following table (Table 1).

Table 1. Summary of Variable Definitions and Data Sources.

Variable Category	Variable Name (Abbreviation)	Definition	Data Source	Description/Notes
Dependent Variable	Average Order Value (AOV)	Daily average net amount paid per order	Transaction-level logs from the store's backend	
Independent Variable	Air Quality Index (AQI)	Daily air quality value in the business location	2345 Weather (A leading third-party meteorological platform) [34]	The platform synchronizes authoritative real-time monitoring data from national meteorological stations and provides historical logs accurate to the "district and county" level. This fine-grained data granularity ensures a high degree of spatio-temporal alignment between the relevant variables and the store's specific geographical location.
Mechanism Variable	Average Item Quantity (Variety)	Daily average number of items included in a single order	Transaction-level logs from the store's backend	For example, an order with "one set meal + one add-on" or "two set meals" counts as two items. From a decision psychology perspective, both represent equal weights of choice breadth. Thus, it is a valid proxy for "buying more."
Mechanism Variable	Average Item Price (AIP)	The average transaction price per individual item within an order	Secondary calculation based on transaction logs $AIP = \frac{AOV}{variety}$	Filters out the influence of item count to determine whether consumers are "buying more expensive" items
Control Variable	Marketing Intensity	A composite index of promotional investments from both the merchant and the platform	Store backend operational dashboard	A weighted score calculated from discount depth, traffic acquisition investment, and real-time conversion rates
Control Variable	Average Temperature	Daily average temperature of the specific date	2345 Weather	Controls for the physiological impact of temperature on food selection
Control Variable	Activity Subsidies	Financial subsidies directly funded by the delivery platform.	Transaction-level logs from the store's backend.	Measures platform-side investment (e.g., universal red envelopes). This represents the financial gap between "merchant revenue" and "consumer out-of-pocket spending," isolating the noise from platform promotional policies
Control Variable	Temporal Factors	A 0–1 dummy variable for calendar cycles.	Calendar information	0 for workdays; 1 for statutory holidays and weekends
Control Variable	Weather	A 0–1 dummy variable for precipitation.	2345 Weather	0 for sunny/cloudy; 1 for rain. No other extreme weather like snow or hail was recorded in the sample

3.3. Preliminary Data Analysis: A "Homogeneous" Comparison Under Strictly Controlled Conditions

In accordance with the *Technical Provisions on Ambient Air Quality Index (AQI) (on trial)* (HJ 633—2012) issued by the Ministry of Ecology and Environment of the People's Republic of China, this study selected a "pure observation group" consisting of 17 days with identical external conditions (all being workdays with sunny weather). These provisions categorize air quality into six levels: Excellent (0–50), Good (51–100), Lightly Polluted (101–150), Moderately Polluted (151–200), Heavily Polluted (201–300), and Severely Polluted (>300). Given that the maximum AQI value recorded in our sample is 175, the observations in this study do not involve the "Heavily Polluted" level or above. By comparing order characteristics across different pollution levels while holding temporal attributes (workdays) and

meteorological backgrounds (sunny weather) constant, we aim to intuitively observe the preliminary trends in order structure and Average Order Value (AOV) as air quality varies (see Table 2).

Table 2. Comparison of Average Order Value (AOV) and its structural components across air quality levels under homogeneous conditions.

Air Quality Level	Sample Size (Days)	Temporal Factor	Weather Condition	Mean AOV	Mean Variety	Mean AIP
Excellent	8	Workday	Sunny	10.2325	2.4	4.2773
Lightly Polluted	5	Workday	Sunny	11.484	2.308	4.9717
Moderately Polluted	4	Workday	Sunny	14.07	2.23	6.4015

Preliminary statistical results (see Table 2) reveal that under highly homogeneous ex ternal conditions, the mean value of AOV exhibits a clear stepwise upward trend as air quality deteriorates from "Excellent" to "Moderately Polluted," rising from 10.23 CNY to 14.07 CNY. Further deconstruction of the internal order structure shows that the sample mean of Average Item Quantity follows a slight downward trajectory during this process, decreasing from 2.40 to 2.23 units. In contrast, the sample mean of Average Item Price (AIP) demonstrates a significant upward jump. These preliminary observations, derived from averaging groups of days under strictly controlled variables, suggest that the reshaping effect of air quality on both the Average Order Value (AOV) and its internal order structure may exist independently of cyclical factors or basic weather interference. This data trend provides direct behavioral evidence for the subsequent full-sample non-linear detection using the machine learning framework.

3.4. Analysis Methodology

To accurately capture the complex and potentially non-linear relationship between air quality and Average Order Value (AOV), this study adopts a robust, data-driven machine learning empirical framework (Random Forest-based Partial Dependence Plot RF-PDP). This methodology is designed to deeply explore how environmental stressors reshape the internal decision-making mechanisms of online spending without relying on the restrictive assumptions of traditional statistical distributions. The specific analysis process is structured into the following three steps:

Step 1: Random Forest-based Model Construction

First, this study utilizes the Random Forest algorithm to construct a non-parametric regression model as the analytical foundation. This algorithm builds multiple independent decision trees $T_b(x)$ through bootstrapping and reduces model variance via ensemble averaging, thereby enhancing robustness in the context of small samples. Its ensemble prediction function is expressed as:

$$\hat{f}(x) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \quad (1)$$

where B is the total number of decision trees, and x is the vector of input features including the independent and control variables.

Step 2: Significance Determination Based on Permutation Test

This study introduces the Permutation test. The core logic involves constructing a "null hypothesis distribution" by randomly shuffling the time series of the independent variable (AQI) 1000 times, thereby severing its actual association with the price. By calculating the percentile ranking of the importance score from the original data (I_{orig}) within the

distribution of scores generated by these random permutations, the p-value of the empirical finding is derived:

$$P = \frac{1}{M}\sum_{m=1}^{M} I\left(Score_{random,m} \geq Score_{orig}\right) \quad (2)$$

If $p < 0.05$, the impact of air quality on AOV is determined to be statistically significant.

Step 3: Influence Quantification Based on Partial Dependence Analysis

Building on the previous steps, the Partial Dependence Plot (PDP) analysis within our RF-PDP framework is implemented to identify and visualize the net marginal effect of AQI. As the core high-precision diagnostic tool of this framework, PDP calculates the average predicted expectation corresponding to AQI by marginalizing the interference of other variables across the entire sample space. This allows for a granular quantification of the response path. The mathematical function for the PDP estimator is defined as follows:

$$\hat{f}_{Xs}(xs) = \frac{1}{n}\sum_{i=1}^{n} \hat{f}(xs, xc, i) \quad (3)$$

In this equation, xs represents the independent variable (AQI), and xc represents all control variables. This method enables the isolation of the pure response path of air quality to AOV and its internal decision-making structure.

4. Results

4.1. The Impact of Air Quality on Online Food Delivery Average Order Value (AOV)

Across the full observation interval (AQI: 13–175) (Figure 2), as air quality deteriorates, the online food delivery Average Order Value (AOV) exhibits a clear upward trend, with the response curve remaining entirely within the confidence interval. The impact coefficient of air quality on AOV is 0.0053. Following simulation experiments involving 1000 random permutations of the time series, the explanatory power of the air quality feature is significantly superior to random noise, yielding a calculated p-value of 0.0000 ($p < 0.001$). This implies that after controlling for the interference of marketing intensity, activity subsidies, average temperature, weather conditions (rainy/sunny), and temporal factors (weekdays/holidays), every one-unit increase in the AQI results in a net growth of 0.0053 CNY in online food delivery AOV. This finding directly addresses the research question regarding price: while air pollution drives a surge in food delivery "volume," the "price" concurrently exhibits an upward trend. That is, air pollution not only increases the volume of food delivery orders but also elevates the spending intensity per order.

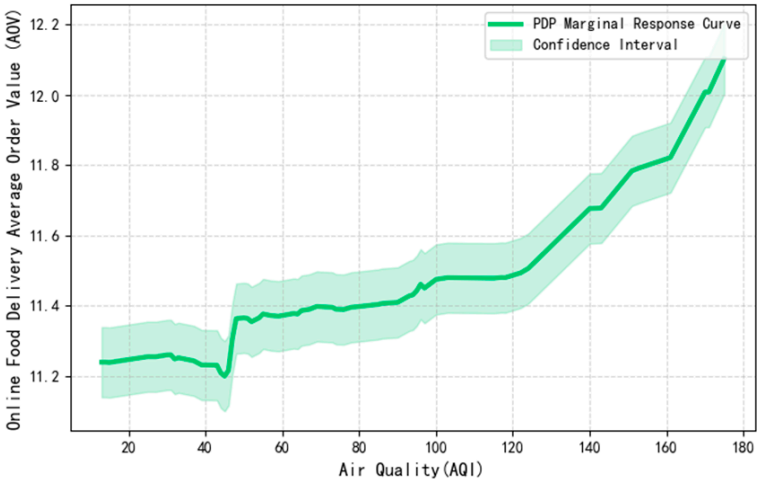


Figure 2. The Impact of Air Quality on Online Food Delivery Average Order Value.

4.2. Robustness Checks

4.2.1. Sample Adjustment: Excluding Extreme Observations

To eliminate the potential bias caused by extreme environmental stressors (outliers), we conducted a robustness check by adjusting the sample. Specifically, observations with AQI values at the extremes—below 30 or above 160—were excluded, and the model was re-estimated using the remaining truncated dataset (Figure 3).

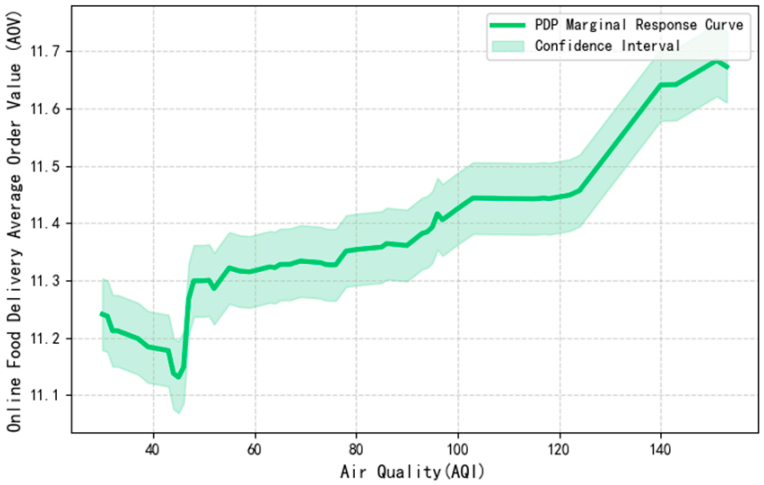


Figure 3. Robustness check: Marginal effect of air quality on AOV excluding extreme observations.

The results indicate that after removing the influence of extreme values, air quality deterioration continues to exert a highly significant positive effect on Average Order Value (AOV), with an average response coefficient of 0.0035 (p = 0.0000). While the magnitude of the coefficient is slightly adjusted compared to the full-sample analysis (0.0053), the directional consistency and statistical significance remain highly robust. This evidence reinforces that the price restructuring logic identified in this study is representative across a standard range of environmental fluctuations and is not an incidental outcome driven by a few idiosyncratic days of extreme AQI.

4.2.2. OLS Regression

To further verify the reliability of the baseline findings obtained from the RF-PDP framework, this study employs Ordinary Least Squares (OLS) regression as an alternative estimation method to re-examine the impact of air quality (AQI) on online food delivery Average Order Value (AOV) (Table 3).

Table 3. OLS Regression result.

	Coefficient	***p*-Value**
Air Quality Index (AQI)	0.0081	0.0036
Marketing Intensity	Controlled	—
Average Temperature	Controlled	—
Activity Subsidies	Controlled	—
Temporal Factors (Holidays/Weekends)	Controlled	—
Weather (Rainy/Sunny)	Controlled	—
R-squared	0.6886	—

The results of the Ordinary Least Squares (OLS) regression demonstrate that the coefficient for the core independent variable, AQI, is 0.0081, with an associated *p*-value of 0.0036 ($p < 0.01$). Additionally, the model exhibits a favorable goodness-of-fit, indicating that the linear specification effectively captures the underlying data patterns. These findings confirm that air quality deterioration leads to a significant increase in the Average Order Value (AOV). Crucially, this result is highly consistent with the directional trends and significance levels obtained through the RF-PDP framework in the primary analysis. The alignment between the traditional parametric estimation and the non-parametric machine learning approach further reinforces the robustness of our core conclusion: environmental stress exerts a stable and significant upward pressure on online food delivery spending intensity.

4.3. Heterogeneity Analysis Across Different Air Quality Intervals

The previous section derived the average coefficient for the impact of air quality on online food delivery AOV. To further deconstruct the dynamic response logic of this impact, this study employs the median AQI value (AQI = 66) as a split point, partitioning the full sample into a "Good Air Quality Zone" and a "Poor Air Quality Zone." The marginal response coefficients for each zone were calculated respectively (Figure 4). The analysis reveals that the response of online food delivery AOV to air quality demonstrates significant asymmetry and acceleration characteristics.

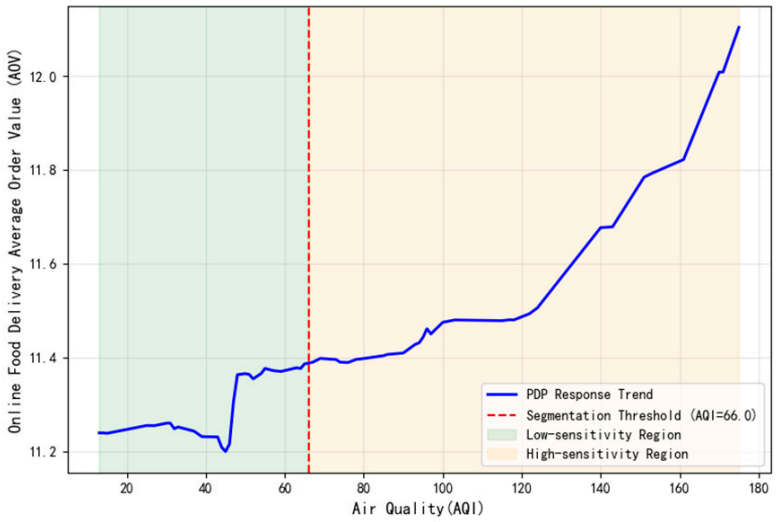


Figure 4. The Segmented Impact of Air Quality on Online Food Delivery AOV.

(1) Good Air Quality Interval (AQI: 13–65)

Within the relatively good air quality interval (AQI < 66), the online food delivery AOV has demonstrated a clear positive growth trend, although its response sensitivity remains at a relatively low level, with an average response coefficient of 0.0028. Specifically, for every one-unit increase in AQI, the AOV increases by 0.0028 CNY. This empirical result indicates that even under lower environmental pressure, consumers' spending logic has already begun to undergo a subtle upward reshaping, though the change at this stage is still in a "gentle adjustment phase." Compared to the high environmental pressure interval, consumers' willingness to expand their spending has not been fully released during this period, and their decision-making behavior exhibits strong robustness.

(2) Poor Air Quality Interval (AQI: 67–175)

Once the air quality index crosses the median threshold and enters the moderate-to-high pollution range, the response coefficient of the online food delivery AOV surges to

0.0066. That is, when the AQI is higher than 66, for every one-unit increase in AQI, the AOV increases by 0.0066 CNY. The price growth in the poor air quality interval is approximately 2.4 times greater than that in the relatively good air quality interval. This sharp jump in the slope confirms that the impact of air quality on the online food delivery AOV is not a uniform cumulative process; instead, it accelerates as the AQI increases. The asymmetric response coefficients across different air quality zones further demonstrate the non-linear characteristics of the impact of air quality on AOV. This proves that the intervention of environmental factors on the bill structure deepens with the accumulation of pressure and undergoes a logical transition from "gentle adjustment" to "strong restructuring" after crossing a specific environmental milestone. This finding provides an important quantitative basis for merchants to identify the explosive point of environmental dividends.

4.4. Mechanism Identification of the Impact of Air Quality on Food Delivery AOV

4.4.1. The Reduction in Average Item Quantity Under Air Quality Deterioration

As air quality deteriorates (AQI increases), the online food delivery AOV rises; that is, the poorer the air quality, the more expensive the orders become. At a deeper level, what drives this increase in AOV? Is it because consumers order a larger quantity of items within a single order? For instance, does ordering a set meal plus additional side items lead to the rise in the order price? To investigate this, we continue to use Random Forest-based Partial Dependence Plot (RF-PDP) to analyze the impact of air quality on the Average Item Quantity.

The empirical results (Figure 5) show that after controlling for variables such as marketing intensity, activity subsidies, average temperature, weather conditions (rainy/sunny), and temporal factors (weekdays/holidays), air quality has a significant negative effect on Average Item Quantity (the influence curve slopes downward to the right and is contained within the confidence interval). The impact coefficient of air quality on Average Item Quantity is −0.0014, and the *p*-value reaches a highly significant level of 0.0000. In other words, for every one-unit increase in AQI, the Average Item Quantity decreases by 0.0014. This means that as air quality deteriorates, it actually leads consumers to exhibit a tendency toward "item simplification" when placing orders. This proves that the impact of air quality on AOV is not caused by consumers ordering a larger quantity of items. When air quality worsens, although consumers order meals online more frequently, they do not "buy more"; on the contrary, they "buy fewer" items when ordering.

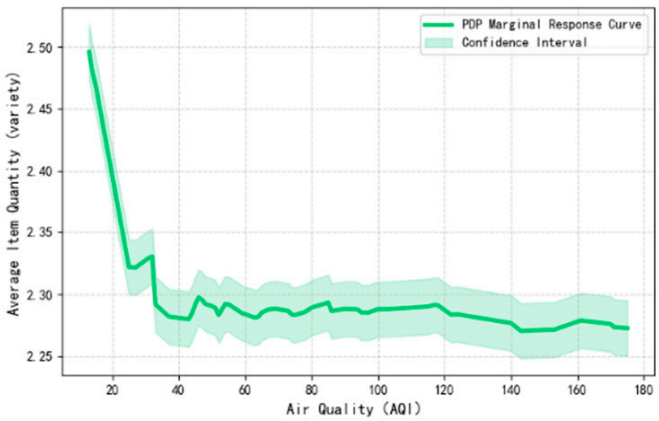


Figure 5. The Net Marginal Effect of Air Quality Deterioration on Average Item Quantity.

4.4.2. The Elevation of Average Item Price Under Air Quality Deterioration

After controlling for marketing intensity, activity subsidies, average temperature, weather conditions (rainy/sunny), temporal factors (weekdays/holidays), and Average

Item Quantity, the influence curve of air quality on Average Item Price slopes upward to the right and is contained within the confidence interval (Figure 6). This is consistent with the trend observed in air quality's impact on online food delivery AOV. The impact coefficient of air quality on Average Item Price is 0.0066 (p = 0.0000). Specifically, for every one-unit increase in AQI, the Average Item Price rises by 0.0066 CNY. This implies that as air quality deteriorates, customers tend to select higher-priced items, thereby "buying more expensive" items. Integrated with the preceding analysis, this confirms that air quality deterioration causes online food delivery orders to exhibit a pattern of "fewer but more expensive items."

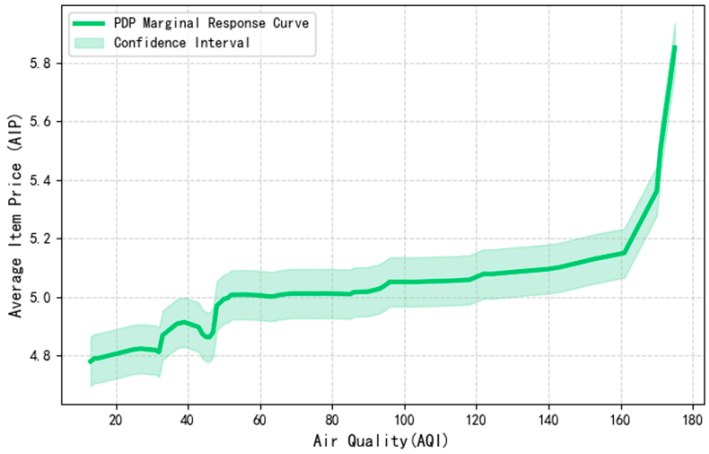


Figure 6. The Increase in Average Item Price Under Air Quality Deterioration.

5. Analysis of Consumers' "Buying Fewer but More Expensive" Behavior

The "buying fewer but more expensive" pattern can be interpreted as a key behavioral logic driving the rise in online food delivery AOV under deteriorating air quality. Air quality deterioration, acting as a significant external stressor, has been associated in existing literature with impaired cognitive function and increased irritability through physiological stress responses [35,36], which may make consumers more susceptible to psychological fatigue. Archsmith et al. further demonstrate that even short-term exposure to air pollution is associated with an increased likelihood of making decision errors and reduced overall cognitive performance [37]. While digital interfaces on e-commerce food delivery platforms provide efficient choice paths, the information-dense "fast-scrolling" menus and complex combinations could potentially evolve into a heavy "decision burden" for consumers under environmental stress [38]. According to bounded rationality theory [39], when individuals experience stress-induced fatigue, their capacity for complex comparative analysis tends to diminish. To conserve limited psychological energy, consumers may exhibit a tendency toward "decision avoidance," actively simplifying the number of items ordered as a heuristic strategy to mitigate cognitive load (i.e., potentially reducing fatigue by buying fewer items) [40]. Consequently, instead of seeking comfort through increased quantity, the observed data suggests that consumers under deteriorating air quality may streamline their order volume to alleviate the fatigue associated with making complex choices.

However, this behavior of "buying fewer" does not necessarily lead to a reduction in total spending. In the digital interface of e-commerce platforms, the lack of tactile and olfactory feedback might mean that when consumers choose to buy fewer items to save effort, they perceive a higher risk of "decision error" (such as a suboptimal culinary experience). This potentially triggers a "need for quality certainty." In other words, consumers may be less willing to expend cognitive effort on meticulously selecting various items, as this would further deplete their mental resources. To hedge against the potential for "decision

errors" associated with "buying fewer," consumers may gravitate toward high-priced "signature premium meals" or "prime ingredients." Vohs and Faber [41] argue that when self-regulatory resources are depleted, individuals may become more impulsive and exhibit a higher willingness to pay for premium rewards as a form of self-soothing. Furthermore, these observations align with the framework of Pettit and Sivanathan [42], which posits that individuals under threat may exhibit a preference for high-status and high-priced items as a "psychological shield." Although the item quantity per order decreases, the high price is often psychologically equated with "low risk" and "high-quality assurance" [43]. This price-quality heuristic likely helps eliminate anxiety regarding decision errors arising from simplified choices. Thus, a plausible interpretation is that consumers under deteriorating air quality opt for more expensive items to offset the perceived risks of a streamlined order.

The information delivery mode of e-commerce platforms likely facilitates this seemingly contradictory ordering behavior. For consumers under environmental stress, the need to constantly "fast-scroll" through menus may be perceived as a burdensome task. To facilitate a quicker exit from this information-dense environment, consumers' defensive instincts might be activated, leading to a simplified order quantity. Tice et al. observe that under emotional distress, mood regulation goals may take precedence over impulse control, prompting a shift away from strict budget constraints [44]. Meanwhile, e-commerce platforms often provide visual reinforcement for high-priced "signature dishes." Alba and Williams point out that such visual salience in digital environments can effectively guide consumers toward high-value choices [45]. This "highlight-oriented" mode may provide a high-certainty exit for consumers suffering from decision fatigue [46]. Through its unique information distribution logic, the platform may induce a "reduction" under cognitive defense while simultaneously guiding a "markup" as a form of risk hedging [47]. Consequently, the e-commerce environment likely facilitates the "buying fewer but more expensive" behavior, contributing to the rise in final AOV.

In Section 4.4.1, this study confirmed that air quality deterioration has a significant negative impact on Average Item Quantity, which aligns with the theoretical expectation of "decision simplification" under stress. The core question that follows is whether this "buying fewer" behavior constitutes a direct inducement for "buying more expensive." To verify this internal transmission path of "substituting quantity with quality," this study treats Average Item Quantity as the core explanatory variable. We utilize Random Forest-based Partial Dependence Plot (RF-PDP) analysis to further detect its contribution to Average Item Price. This step aims to isolate external interference and identify whether a statistically robust causal continuation exists between "buying fewer" and "buying more expensive."

The empirical results (Figure 7) indicate that the influence curve of Average Item Quantity on Average Item Price exhibits a clear downward trajectory, with the response path and its confidence interval remaining highly stable. The calculated average impact coefficient is -1.098 ($p = 0.0000$). This significant negative association suggests a strong causal link where a reduction in Average Item Quantity is followed by a jump in Average Item Price. Specifically, for every one-unit decrease in Average Item Quantity, the Average Item Price within the order increases by an estimated CNY 1.098. These findings point to a decision-making logic where "buying fewer" appears to be a precursor to "buying more expensive".

This result is consistent with a "substituting quantity with quality" compensation mechanism within the price "black box." A plausible interpretation is that when the psychological fatigue likely induced by air quality deterioration steers consumers toward a "decision avoidance" mode—leading them to streamline the number of items they select—a "risk defense" motive may be simultaneously activated. To ensure that a simplified order

does not lose its sense of reward or result in a suboptimal experience due to limited variety, consumers may develop an increased demand for quality certainty. This demand appears to manifest as a "vertical premium willingness," where consumers opt for higher-priced, sensory-stimulating items to "bridge" and potentially cover the value gap left by the reduction in variety.

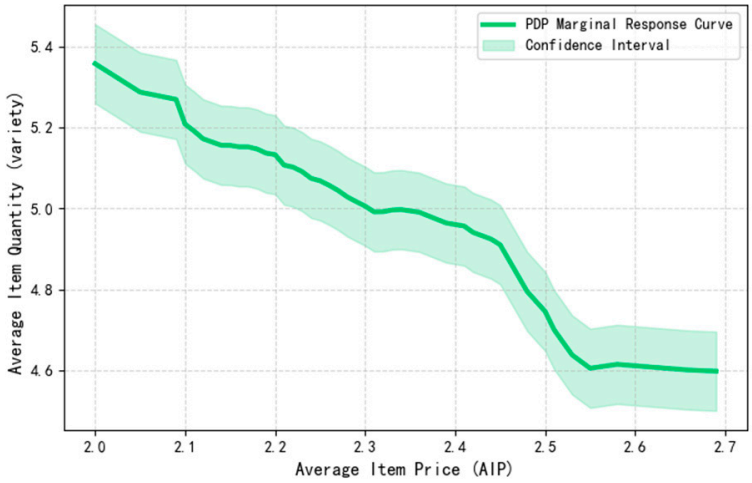


Figure 7. Elevation of Average Item Price Induced by the Reduction in Average Item Quantity.

The identification of this causal coefficient provides an empirical foundation for the decision-making logic proposed in this study and completes the overall analytical framework. As illustrated in Figure 8, the data suggests a plausible pathway where psychological fatigue, potentially induced by air quality deterioration, may steer consumers toward a "defensive contraction" at the "volume" level, leading to the observed simplification of Average Item Quantity. To mitigate the potential experience risks associated with such simplified choices, consumers appear to simultaneously initiate a "quality-oriented response" on e-commerce platforms, redirecting saved cognitive resources to prioritize an upward shift in Average Item Price.

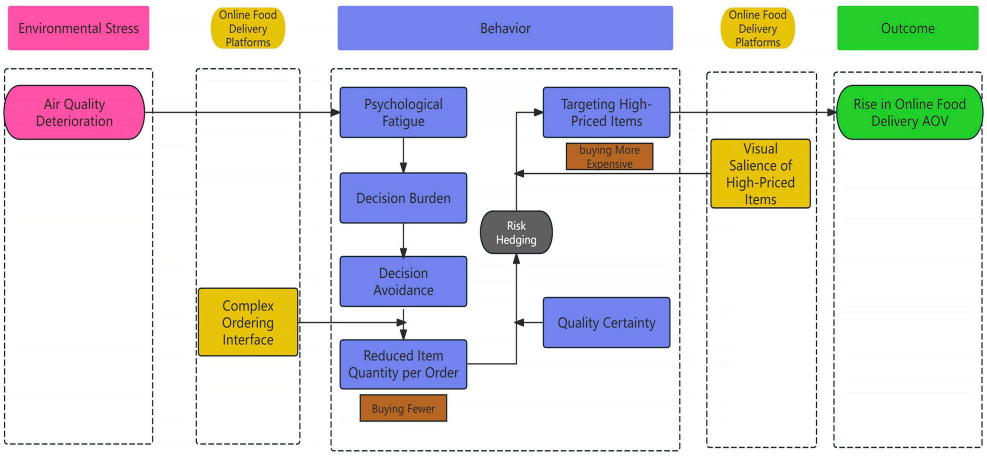


Figure 8. Behavioral Mechanism of "Buying Fewer but More Expensive" in Response to Environmental Stress.

Consequently, the observed rise in AOV may not represent an isolated or disordered price fluctuation. Rather, it can be viewed as a strategic value restructuring through which consumers appear to balance decision efficiency and quality assurance under the catalyst of environmental pressure. This proposed transmission mechanism—characterized

by "environmental stress driving quantity reduction and risk aversion inducing quality enhancement"—offers a consistent explanation for the causal connotation behind the divergent phenomenon of "buying fewer but more expensive".

6. Conclusions and Management Implications

6.1. Research Conclusions

Utilizing micro-transactional data from a food delivery store and employing machine learning methods such as Random Forest and Partial Dependence Plots (PDP), this study explores and deconstructs the impact and mechanisms of air quality on Average Order Value (AOV). The conclusions are summarized as follows:

(1) Air quality deterioration significantly drives up online food delivery AOV, exhibiting non-linear acceleration characteristics.

Air quality (AQI) has a significant positive driving effect on AOV, with a global average response coefficient of 0.0053 (p = 0.0000). This reshaping effect shows distinct asymmetry across different environmental stress intervals: using the median AQI (66) as a split point, the response intensity of AOV in the poor air quality interval (0.0066) is approximately 2.4 times that of the good air quality interval (0.0028). This confirms that the objective impact of environmental stress on e-commerce bill structures accelerates as pollution levels deepen.

(2) The behavior of "buying fewer but more expensive" supports the rise in online food delivery AOV.

The impact of air quality on consumption behavior reveals a directional divergence: air quality deterioration has a significant negative impact on Average Item Quantity (-0.0014) but a strong positive drive on Average Item Price (0.0066). This implies that under deteriorating air quality, consumers do not seek comfort by increasing the number of items ordered; instead, they choose to "buy fewer" items while simultaneously "buying more expensive" ones.

(3) The underlying cause of "buying fewer but more expensive" is that "buying fewer" triggers "buying more expensive."

Deep behavioral analysis further reveals that Average Item Quantity has a highly significant negative driving effect on Average Item Price, with a coefficient as high as -1.098 (p = 0.0000). This quantitative evidence suggests that "buying more expensive" is essentially a chain reaction triggered by "buying fewer": when cognitive load induced by environmental stress leads consumers into a "decision avoidance" mode and causes them to simplify the variety of items ordered, they develop a strong demand for "quality certainty" to hedge against potential experience risks resulting from simplified decisions. This leads them to spontaneously concentrate their budget on high-value core items.

6.2. Management Implications

The above conclusions provide the following insights for the precision operations of food delivery merchants in dynamic environments:

(1) Establish a dynamic operational system based on environmental monitoring to strategically optimize profit structures using environmental dividends.

Empirical results demonstrate that air quality deterioration provides a window of opportunity to enhance food delivery AOV. However, merchants must remain highly cautious when capturing these dividends. Considering the sensitivity of consumers' mental accounts regarding spending ceilings for specific categories, aggressive or explicit price adjustments that cross a consumer's psychological threshold can easily trigger a sense of

"Price Unfairness." This may, in turn, drive consumers into a defensive frugality mode, leading to a sharp decline in both purchase volume and total expenditure.

Therefore, this study suggests that merchants should avoid blunt, across-the-board price increases and instead achieve more robust premium capture through "value structure restructuring." Specific strategies include: first, implementing "differential discount contraction"—leveraging the rigid demand for "quality certainty" under environmental stress to moderately reduce discounts or promotional intensity for high-end signature dishes, thereby securing profit margins through natural premiums. Second, optimizing the "value-based ranking on digital interfaces" by utilizing algorithms to place high-AOV, highly rated core items in visually salient positions. This type of "strategic selection guidance" effectively aligns with consumers' spontaneous tendency to "buy more expensive" items in stress-induced states.

(2) Optimize dynamic product curation and ranking logic: transition from "quantity-driven" to "value-relevance."

Given that consumers exhibit the "buying fewer but more expensive" trait under deteriorating air quality, merchants should optimize their store-level product presentation strategies to better serve these evolving preferences. Although global platform algorithms are typically beyond a single merchant's control, store owners can utilize available digital tools to curate their own storefronts—for instance, by prioritizing high-value signature items in the "Must-order" section. Since consumers under these environmental conditions appear to value individual item quality over variety, this strategic alignment allows merchants to provide more relevant and higher-quality options to meet consumers' heightened demand for quality assurance. Simultaneously, merchants themselves can also increase their revenue.

(3) Implement "decision navigation" on store pages to alleviate cognitive friction and enhance ordering efficiency.

The study suggests that the observed "buying fewer" pattern reflects an adaptation to psychological fatigue under deteriorating air quality. To assist consumers who streamline their item quantity to save effort, merchants should focus on reducing cognitive friction within their digital menus. Specifically, merchants can implement "decision navigation" by applying clear quality-assurance labels (e.g., "Quality Guaranteed" or "Signature Selection") to key products. By optimizing the presentation of information and providing reliable quality signals, merchants can help consumers identify high-value options more efficiently, thereby addressing the potential need to hedge against decision risks. To ensure a consistent user experience, these navigational aids should be treated as convenience tools that support the decision-making process. Merchants should ensure that the full menu remains accessible, providing transparency while guiding consumers toward higher-quality choices.

6.3. Research Limitations and Future Research Outlook

6.3.1. Research Limitations

Although this study utilizes first-hand micro-transaction trajectories to deeply deconstruct the price "black box," several limitations remain:

(1) Limitations in Universality and Representativeness.

This study is based on continuous operational data from a single city (Fuling Dis- trict, Chongqing) and a single catering category (Spicy Hot Pot). While the "modular ordering" feature of Spicy Hot Pot provides an ideal experimental field for observing the subtle reshaping of spending structures, consumers in different categories (such as standardized fast food or milk tea/drinks) or in cities of different tiers may exhibit heterogeneous behaviors when facing environmental stress.

(2) Inferential Nature of Consumer Behavior.

Since this study utilizes backend transaction logs rather than direct psychological measurement data from consumers, the analysis of motivations such as "psychological fatigue" and "risk hedging" is essentially a plausible interpretation and theoretical deduction based on the high alignment between empirical trends and existing theories. Although this logic is supported by causal transmission paths at the empirical level, the rigor of the research conclusions at the psychological level still needs further reinforcement due to the lack of direct observation of consumers' instantaneous psychological states.

(3) Insufficient Dynamic Coverage of Environmental Variables.

This study primarily focuses on the instantaneous reshaping effect of air quality on Average Order Value (AOV). According to environmental psychology research, the psychological load caused by air quality typically exhibits both "same-day immediacy" and "short-term accumulation" (usually lasting 24–48 h). Given that food delivery consumption is characterized by a high degree of immediate gratification, this paper mainly captures the instantaneous qualitative shifts in decision-making brought by same-day environmental stress, without fully considering the potential "psychological depletion" lag effect that continuous deteriorating air quality may have on spending structures.

6.3.2. Research Outlook

Based on the aforementioned limitations, future research can be deepened in the following directions:

(1) Cross-validation across multiple categories and regions.

Future research plans to expand the empirical scope to joint observations of multiple brands and categories and compare the differences in environmental tolerance among consumers in different regions. Through cross-context comparisons, we aim to verify the generalizability of the "reducing quantity while enhancing quality" model in various e-commerce scenarios and construct a more universal environmental stress decision-making model.

(2) Directly Obtaining Consumer-side Data.

The author plans to seek first-hand consumer-side data in the same region in future studies. By directly acquiring consumer data during the ordering process, the "decision avoidance" and "risk hedging" logic proposed in this paper can be verified with stronger evidentiary power, thereby elevating the research from "behavioral inference" to "causal confirmation."

(3) Detection of Lag Effects in the Time Dimension.

Future research could introduce Distributed Lag Models to further detect the cumulative impact of environmental stress on bill structures and its recovery cycle. By analyzing how environmental stress diminishes over time or produces sustained psychological impacts, more forward-looking environmental marketing decision support can be provided to merchants.

Author Contributions: Conceptualization, Y.W.; methodology, Y.W.; software, Y.W.; validation, Y.W., J.L. and M.Y.; formal analysis, Y.W.; investigation, Y.W.; resources, Y.W.; data curation, Y.W.; writing—original draft preparation, Y.W.; writing—review and editing, Y.W.; visualization, Y.W.; supervision, M.Y.; project administration, J.L.; funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: National Natural Science Foundation of China: 71964032.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data are not publicly available but are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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