Complexity

Complexity and Contemporary Marketing Matters

Lead Guest Editor: Ning Chen
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Hindawi
Complexity
Volume 2022, Article ID 4905287, 11 pages
https://doi.org/10.1155/2022/4905287

Research Article

The Effect of Government Subsidies on Firm R&D Investment in China: From Perspectives of Ownership and Market Power

Haijing Wang,[1] Junguo Shi,[1] Muhammad Imran,[2] Jiaqi Gao,[3] Yitian Zhang,[4] and Rongyu Wang[2]

[1]*School of Finance and Economics, Jiangsu University, Zhenjiang 212013, Jiangsu, China*
[2]*Information Research Institute, Qilu University of Technology (Shandong Academy of Sciences), Jinan 520014, Shandong, China*
[3]*Business School, Shenyang University, Shenyang 110044, China*
[4]*School of Business Administration, Northeastern University, Shenyang 110819, China*

Correspondence should be addressed to Muhammad Imran; imran@sdas.org

Received 4 January 2022; Revised 16 May 2022; Accepted 11 August 2022; Published 25 August 2022

Academic Editor: Ning (Chris) Chen

This study examines the effects of government innovation subsidies under different combinations of market power (i.e., the relationship between enterprises, upstream suppliers, and downstream customers) and different types of ownership from the perspective of the contemporary marketing microenvironment. Based on the panel data of listed Chinese manufacturing companies from 2009 to 2018, the empirical results show that, in the case of higher buyer power, government subsidies will significantly promote the R&D investment of enterprises and the positive effect is not affected by nature of the enterprise's ownership. In the case of lower buyer power and seller power, government subsidies significantly promote the R&D investment of nonstate-owned enterprises, but have no effect on state-owned enterprises. The conclusions of the study further verify that, under different combinations of market power, there are significant differences in the effects of innovation subsidies for enterprises with different forms of ownership, and these provide a theoretical point of reference for the government to implement innovation subsidies. This study not only fills the theoretical black box of the relationship between government subsidies and enterprise innovation but also provides relatively new empirical evidence for the related research on innovation subsidies in developing countries.

1. Introduction

In the context of high-quality development, how to stimulate the innovation vitality of microeconomic entities, promote enterprises' reform and innovation, improve the innovation quality of microenterprises, and further play the role of innovation as the "engine" driving China's economic transformation and upgrading? These have become important practical issues for China in order to implement an innovation-driven development strategy. In recent years, China's government subsidies in stimulating enterprise innovation have shown an increasing trend. According to data from the Wind Database, over the period 2009–2018, the amount of government subsidies received by all A-share listed companies increased from 30.14 billion yuan to 167.17 billion yuan, and the proportion of A-share listed companies receiving government subsidies increased from 44.7% to 98.2%. The intensity and breadth of government subsidies in China are certainly increasing.

The effect of government innovation subsidies has always been an important research issue and has been of wide concern in academia. The externality theory of R&D activities proposed by Arrow [1] laid the foundation for the economic theory of government intervention in R&D innovation activities of enterprises. Market failure is widespread as a result of the externality and uncertainty of such activity[2]. Earlier research demonstrated that such market failure will prevent enterprises from achieving the socially optimal level of R&D [1, 3]. To solve the problems of market failure in R&D and the insufficient supply of effective innovation, the government has often adopted a policy of innovation subsidies to compensate for the economic losses caused by the "market failure" of enterprises, reducing the innovation risk of enterprises, and encouraging enterprises to improve innovation [4]. Government subsidy is also a common policy means to encourage enterprise innovation, and is the most direct form of a government's "helping hand".

However, there has not been a broad consensus on the effect of government innovation subsidies. Some scholars believe that government subsidies can effectively alleviate financing difficulties and market failures faced by enterprises in the process of innovation. From the viewpoint of resources, government subsidies can increase the R&D investment of enterprises by directly supplementing innovative resources [5, 6]. In addition, based on the signal theory, government subsidies may serve as a certification signal to further help enterprises obtain external investment [7]. Meanwhile, since technology and knowledge are characterized by the spillover of public goods, nonexclusivity of results and nonexclusivity of benefits, enterprises' investment in R&D will inevitably be affected by market failure and underinvestment. Government subsidies can also, to some extent, rectify the externality and exclusivity of enterprise innovation [1]. In other words, government subsidies can share the R&D costs and risks of enterprises, make up for the costs of innovation activities caused by externalities, and then promote enterprise innovation [8].

In addition, government subsidies can stimulate innovation competition among enterprises and produce an "incentive effect" and "seed effect" [9]. Others suggest that government subsidies will distort the allocation of market resources: they may stifle enterprises' private investment in innovation, hence impeding the sponsored firm's innovation capabilities [10, 11]. The government usually grants innovation subsidies for subsidy-designated projects. Therefore, for the consideration of marginal cost, enterprises will choose to apply for R&D projects in the subsidy category formulated by the government, resulting in the government-subsidized projects replacing the R&D innovation projects planned by enterprises themselves, and thus crowding out those enterprises' R&D [12]. Enterprises that receive government subsidies do not need to invest too much money in government-subsidized R&D and innovation projects, and the marginal cost of innovation is almost zero. This may lead to enterprises' dependence on government subsidies, thus crowding out their independent innovation to an extent [13]. At the same time, due to asymmetry of information, the government will inevitably encounter aberrations in the selection of subsidy objects, and a "wrong" subsidy will lead to "subsidy-type development", rather than innovation-type development of subsidized enterprises or industries [14].

Due to the immature institutional environment and rapidly transforming factor and product markets, this contradiction is especially pronounced in economies in transition [15]. Accordingly, the first objective of our research is to investigate whether or not government innovation subsidies in China are efficient.

After reviewing a large volume of relevant literature, Zúñiga-Vicente et al. [16] point out that the main reasons for the differences in research conclusions may be differences in variable selection, research background (countries, industries, time periods), and empirical methods. Based on this conclusion, academia has begun to explore the mechanism of government subsidies from different perspectives. Market power and ownership are the two research perspectives focused on in this study.

Market power and enterprises' innovation activities (i.e., the effect of government innovation subsidies) are inseparable. Each element of a product's production is closely linked. Enterprises, upstream suppliers, and downstream customers comprise a significant component of the contemporary marketing micro-environment. At the same time, upstream and downstream industrial relations (i.e., market power) will inevitably affect the innovation decisions of enterprises. In addition, market power largely determines the profit realization and distribution of innovation activities, thus affecting the decision-making of enterprise innovation activities [17]. It has been pointed out that the effects of government innovation subsidies and R&D activities of enterprises are affected by different degrees of market power [18–23].

However, existing research has some obvious limitations. First, previous studies have only focused on a single aspect of market power (buyer power or seller power), rarely considering both two types of market power together. The reality is that, with the continuous refinement of the social division of labor, an enterprise will face both buyer power and seller power in the market. Thus, these cannot be easily separated in the analysis of the relationship between market power and innovation subsidies. Second, these studies are all carried out in the context of less government intervention. In fact, developing countries rely heavily on government intervention to promote the development and innovation capability of enterprises and industries, such as with the telecommunication equipment provider industry in China [24]. When we consider government intervention (government subsidies), the impact of market power on R&D activities is not fully demonstrated. This leads to the second objective of this research, which is to explore whether government innovation subsidies enhance enterprise R&D intensity under different market power in China.

In emerging economics, enterprises of varying ownership, such as state-owned enterprises, collectively owned enterprises, privately owned enterprises, and foreign-owned enterprises, coexist in the market [25]. The management and resource acquisition capacities of enterprises with different types of ownership vary considerably [26]. The Chinese market has been evolving towards a more mature-free market through reforms for over a decade and, therefore, this inevitably leads to the typical phenomenon of the coexistence of enterprises with multiple ownership forms, which also leads to a very complicated relationship between government subsidies and enterprise innovation. State-owned enterprises and nonstate-owned enterprises have very distinct resource endowments and institutional logics and these may result in their divergent responses to government subsidies. In other words, the form of enterprise ownership is an especially key factor in the utility of government subsidies [27].

As one of the fastest-growing transitional economies, China has a large number of state-owned enterprises. State-owned enterprises are controlled and managed by the local or central government and have natural links with the government. As a pillar of the national economy, state-owned enterprises shoulder the important task of economic development and maintaining social fairness and stability. Therefore, when state-owned enterprises face losses, the government will lend a helping hand by giving them additional subsidies or tax incentives to tide them over. State-owned enterprises in China are always criticized for their privileges in the case of bank loans, investment and financing, government subsidies, and so on [28]. From the perspective of subsidy tendency, in large industrial enterprises the government usually provides tax reduction or various types of subsidies for state-owned enterprises, and that subsidy is relatively large–much higher than that of enterprises with other ownership properties [29]. However, previous studies have shown that state-owned enterprises have received more innovation subsidies, but they have not reached a corresponding level of R&D investment [30, 31]. In addition, nonstate-owned enterprises will also be subsidized by the government for innovation, but the effect of those subsidies has not been effectively demonstrated. Therefore, the third objective of our research is to investigate the efficiency of government subsidies between state-owned enterprises and nonstate-owned enterprises with regard to market power.

In general, previous research investigating the relationship between market power, ownership, and the efficiency of government innovation subsidy is limited in the following respects. First, whether Chinese government innovation subsidies can increase the R&D intensity of enterprises remains a question worth discussing. Second, it is of great significance to test the effect of market power on innovation subsidy efficiency. However, the effect of market power on innovation subsidy efficiency has not been fully tested in previous literature. As far as we are able to determine, our study is the first to explore the effect of government innovation subsidies for both buyer power and seller power in China. Last, but not least, most studies only focus on the relationship between market power and innovation subsidy efficiency, or ownership and innovation subsidy efficiency. There is no literature that simultaneously considers the innovation subsidy effect of different ownership enterprises in response to different market forces.

This study takes Chinese manufacturing A-share listed companies during a specific period (2009–2018) as research samples, in order to further investigate the effect of government innovation subsidies on enterprises with different ownership forms under different market power conditions (buyer power and seller power), on the basis of existing research on market power. All enterprises are divided into two groups, according to their nature of ownership: SOEs and non-SOEs. The empirical results show that, in the case of higher buyer power, government subsidies will significantly promote the R&D investment of enterprises, and the positive effect is not affected by the nature of ownership. In the case of lower buyer power and seller power, government subsidies significantly promote the R&D investment of non-SOEs, but have no effect on SOEs. This research will enhance our knowledge of the effects of government innovation subsidy in China. Our findings will also provide a theoretical basis for policymakers in developing countries to formulate innovation subsidy policies.

The remainder of the study is organized as follows. Section 2 constructs the theoretical model for the study. Section 3 presents the regression model, data sources, and variable definitions. Section 4 shows the descriptive statistics of the main variables and the empirical analysis results. Section 5 contains concluding remarks, including policy implications and research directions for the future.

2. Theoretical Model Design

Based on the conceptualization of González and Pazó [32]; this study introduces market power and ownership as explanatory variables in the empirical study of government subsidies and enterprise innovation, and constructs a theoretical model of government subsidies and market power on R&D investment of enterprises with different ownership models.

Let us suppose there is an industry that is composed of n enterprises, and each enterprise is producing heterogeneous goods whose output is denoted by q_i $(i = 1, 2, \ldots, n)$, and product quality is s_i. The utility function of the consumer is as follows:

$$U(q, s) = \left[\sum_{i=1}^{n} \left(q_i s_i^{\delta}\right)^{\rho}\right]^{1/\rho}, \quad 0 < \rho < 1,\ \delta > 0, \tag{1}$$

where, in accordance with previous research [33]; δ is the sensitivity coefficient of consumers to product quality, and p_i represents the product pricing of the enterprise. On the premise that consumer consumption level Y is given, the demand function of the enterprise can be obtained from the condition of consumer utility maximization as follows:

$$q_i(p, s) = y p_i^{-\eta} s_i^{\varepsilon} M, \tag{2}$$

where $p = (p_1, \ldots, p_n)$, and$\eta = 1/(1-\rho)$ represents the price elasticity of consumer demand. Therefore, $1/\eta$ is the Lerner index, i.e., market power. $\varepsilon = \delta(\eta - 1)$ represents the quality elasticity of consumer demand. Assuming that y is the total number of products that consumers can purchase, then

$$y = Y p^{-1}, \tag{3}$$

where $p = \sum_{i=1}^{n} (p_i/s_i^{\delta})^{1-\eta}$ is the overall price index after considering quality factors. Since demand is positively and monotonically decreasing with quality $(\partial q_i/\partial s_i \rangle 0$, $\partial^2 q_i/\partial s_i^2 \leq 0)$; from this, we can obtain $\delta \leq 1/(\eta - 1)$. If we assume that the number of firms that operate in an industry is sufficient for the price and quality decisions of a single firm to have minimal effects on the aggregate price index p, then the price and quality elasticity perceived by each firm will be identical to η and ε.

Quality can be improved by incurring R&D expenditure, according to some technological rules. Assume that $\overline{x}$ is the effective point of investment in innovation. Enterprises improve their product quality through technological innovation activities, and when their innovation investment is below this specific level $\overline{x}$, the improvement in product quality is not significant (R&D activities have no effect) and product quality is at the same level as it would be without innovation investment (s_0). When the investment in innovation exceeds a specific level $\overline{x}$, product quality is improved and the law of diminishing marginal returns is satisfied. Therefore, the relationship between innovation input and product quality is as follows:

$$s(x_i) = \begin{cases} \overline{x}^{\theta}, & 0 \le x_i \le \overline{x}, \\ x_i^{\theta}, & x_i \ge \overline{x}, \end{cases} \tag{4}$$

where θ is the qualitative elasticity of innovation inputs ($\theta \le 1$). That is, quality can be enhanced, albeit at a declining pace, by incurring extra expenditures in excess of a minimum level $\overline{x}$ (set-up costs) necessary to affect quality.

It is believed that each product can be manufactured at a unit cost c. Assume that, given the activities of the competitors, the enterprise simultaneously picks the price of the product and the degree of R&D expenditure to influence quality. The objective function of the enterprise is as follows:

$$\max_{p_i, x_i} \pi_i = (p_i - c) q_i [p_i, s(x_i)] - x_i. \tag{5}$$

The government will provide subsidies to selected enterprises in order to encourage them to engage in innovative activities. The purpose of the subsidy is to reduce the production cost of enterprises and to stimulate their investment in R&D. Enterprises generally employ a portion of the subsidies for production and a portion for R&D. Thus, the government subsidies have two effects: the cost reduction effect (the unit production cost of the enterprises changes to αc, $0 \le \alpha \le 1$) and R&D incentive effect (after obtaining the subsidies, the total R&D investment of the enterprises is x_i', of which, the investment of the enterprises' own fund is $\beta x_i'$, $0 \le \beta \le 1$). At this stage, the maximization criteria of the enterprises are as follows:

$$\max_{p_i, x_i} \pi_i = (p_i - \alpha c) q_i [p_i, s(x_i)] - \beta x_i'. \tag{6}$$

In the face of government subsidies, rational enterprises will determine the optimal product price p_i^* and the amount of innovation investment x_i^* according to equation (6). Enterprises may also opt not to engage in innovation activities, in which case the quantity of innovation input $x_i^* = 0$. Combining the above two cases, the enterprise will choose the optimal price and innovation input combination (p_i^e, x_i^e) to achieve the goal of profit maximization, such that

$$\pi_i (p_i^e, x_i^e) = \max\{\pi_i (p_i^*, x_i^*), \pi_i (p_i^{**}, 0)\}, \tag{7}$$

where p_i^{**} is the product price that the enterprise will set if it decides not to undertake R&D activities.

It will be observed that the firm only invests in R&D when doing so is the most profitable option. Enterprises choose to increase their R&D investment when the benefits from their choice of innovation activities are higher than if they do not undertake innovation activities, i.e., $\pi_i (p_i^*, x_i^*) > \pi_i (p_i^{**}, 0)$. Taking the derivative of p_i and x_i' in equation (6), the price and innovation input level in equilibrium can be calculated as follows:

$$p_i^* = \frac{\eta \alpha c}{(\eta - 1)}, \tag{8}$$

$$x_i^* = \left(\frac{\theta \varepsilon}{\eta \gamma \beta}\right)^{1/1-\theta\varepsilon} \overline{x}, \tag{9}$$

where $\gamma = \overline{x}/p_i^* q_i (p_i^*, s_0)$ is the ratio of the effective point of innovation investment to sales revenue at an optimal price and standard quality. At this point, $p_i^* = p_i^{**}$. Substitute p_i^* into equation (5), and the following equation can be obtained according to the Dorfman–Steiner condition:

$$x_i^{\theta\varepsilon - 1} = \frac{\eta - 1}{c \theta \varepsilon y p^{-\eta}}. \tag{10}$$

By substituting equation (10), we can obtain:

$$\pi_i (p_i^*, x_i') = \left(\frac{1 - \theta\varepsilon}{\eta}\right) y p_i^{* -\eta + 1} x_i^{\theta\varepsilon}, \tag{11}$$

$$\pi_i (p_i^{**}, 0) = \frac{1}{\eta} y p_i^{* -\eta + 1} \overline{x}^{\theta\varepsilon}. \tag{12}$$

According to equations (11) and (12), when $x_i^{**} = \overline{x}/(1 - \theta\varepsilon)^{1/\theta\varepsilon}$, enterprises will receive the same benefits from innovation activities as they would have if they had not done so. As a result, an enterprise must satisfy $x_i^* \rangle x^{**}$ when choosing innovation initiations. That is, to convert to the following condition:

$$\frac{1}{\eta \gamma \beta} > (\theta\varepsilon)^{-1} (1 - \theta\varepsilon)^{-1 - \theta\varepsilon/\theta\varepsilon}. \tag{13}$$

According to equation (13), when the government subsidy is 0, $\beta = 1.\beta < 1$ means that the enterprise receives subsidies, and the R&D cost of the enterprise decreases. Therefore, the probability of innovation in the enterprise will be increased. At the same time, it can be seen that the probability of enterprise innovation activities is positively correlated with market power $1/\eta$ (i.e., the Lerner index).

When an enterprise decides to invest in R&D, it will determine the optimal level of R&D investment. Accordingly, an enterprise's optimal R&D intensity (i.e., the ratio of R&D investment to sales revenue) can also be calculated.

$$R_i^* = \frac{x_i^*}{p_i^* q_i^*}. \tag{14}$$

According to equation (2), the following equation can be obtained:

$$q^* = yp^{*-\eta}x_i^{*\theta\varepsilon}. \quad (15)$$

Substitute equations (8), (9), and (15) into equation (14) to obtain the R&D intensity of the enterprise when the market is in equilibrium:

$$R_i^* = \frac{\theta\varepsilon}{\beta\eta}. \quad (16)$$

As can be seen from equation (16), when an enterprise decides to invest in R&D, its R&D intensity is affected by government subsidies and market power: the greater the government subsidies are, the smaller the coefficient β is, and the greater the R&D intensity of the enterprise will be. At the same time, the stronger the market power $1/\eta$, the greater the intensity of R&D expenditure.

It is important to note that, among the determinants of R&D investment, market power $1/\eta$ and product quality elasticity of demand ε are both closely related to industry attributes. The R&D capability θ and threshold $\overline{x}$ of an enterprise are all dependent on the individual characteristics of the enterprise, such as enterprise scale, profitability, financial status, and operating years. Of these, the nature of ownership is a core element that needs special consideration.

Therefore, based on the theoretical models mentioned above, two theoretical hypotheses can be obtained in this study:

H1: The stronger the market power, the more obvious the effect of government subsidies.

H2: Under different market power, enterprise ownership will affect the effect of government subsidies.

3. Research Design

3.1. Sample Selection and Data Sources. This study uses data from China's A-share listed manufacturing enterprises as research samples to investigate the effect of innovation subsidies for enterprises of different ownership in the face of different market power. All sample data were downloaded from the Wind Database. In China, manufacturing enterprises are the main objects of government innovation subsidies. Moreover, the sample number of listed manufacturing companies is relatively large, the listing time is the longest, and the data of annual reports are more mature. Since 2009, the China Securities Regulatory Commission (CSRC) has required listed companies in China to disclose the names of their top five customers and suppliers in their annual reports. However, due to the impact of COVID-19, data disclosure in the 2019 and 2020 annual reports is incomplete and the data quality is questionable. Therefore, this study determined the research period to be from 2009 to 2018. Before the empirical analysis, the initial data were processed, and the sample observation objects that did not meet the requirements were eliminated according to the following criteria. First, enterprises with ST marks were removed: the ST mark means "Special Treatment"; listed companies with such markings frequently experience abnormal financial conditions or are at risk of delisting. Second, enterprises with fewer than 10 employees were removed: listed companies with too few employees are typically "shell companies," and their pertinent statistics are unworthy of examination. We removed enterprises lacking important financial indicators: samples lacking crucial financial indicators required for this research are atypical and must be discarded. As a result of these decisions, a total of 5697 observations were obtained from 1503 listed companies.

3.2. Variable Selection and Description

(1) *Explained variable*: This study mainly investigates the incentive mechanism of government subsidies on enterprise R&D. Therefore, the explained variable in this study is expressed by the intensity of enterprise R&D investment. R&D investment intensity represents the degree of effort made by an enterprise to improve its innovation capability. Considering the large gap between listed companies in terms of enterprise scale and income level, in order to reduce the estimation bias caused by enterprise heterogeneity, this study uses the proportion of enterprise R&D investment in the main business income of enterprises to measure the intensity of enterprise R&D investment.

(2) *Explanatory variables and moderating variables*: The explanatory variables selected in this study include government subsidy intensity (GOV) and enterprise ownership nature (SOE). In order to investigate the different effects of government subsidies for enterprises of different ownership in the face of different market power, this study takes market power as a moderating variable. The government subsidy intensity (GOV) is expressed by the ratio of government subsidy income to the main business income in the annual report of listed companies. One advantage of using a ratio measure is that it reduces the statistical bias caused by large differences in the amount of government subsidies given to firms of different sizes. Business ownership is a 0-1 variable. According to the nature of listed companies registered, central SOEs, provincial SOEs, prefectural SOEs, and other SOEs are all classified as SOEs, and the value is 1. Other enterprises, as private enterprises, are assigned a value of 0.

Market power refers to the ability of enterprises to control the price of goods when they trade. According to the upstream and downstream relations of commodity trading, market power can be divided into buyer powers for upstream enterprises and seller powers for downstream enterprises. In this study, the proportion of total sales of the top five customers (MC) and the proportion of total procurement of the top five suppliers (MS) are adopted as the proxy variables of seller power and buyer power, respectively. It is worth noting that the larger the value of MC and MS, the smaller the corresponding market power is. For example, the higher the proportion of the total sales of the top five customers (MC), the higher the dependence of the enterprise on the major customers is, the worse the bargaining power and negotiation ability of the enterprise is, and the stronger the customer's control over the enterprise is, and thus the weaker the seller power of the enterprise is. Therefore, it is feasible to use these two proxy variables to represent the market power.

(3) *Control variables*: In order to minimize the bias of empirical results, several control variables are also selected. The control variables used in this study mainly include: (i) enterprise scale (SIZE), measured by the natural logarithm of employees; (ii) enterprise profit ratio (PROFIT), measured by the ratio of total profits to total assets; (iii) enterprise age (AGE), measured by the year minus the year of establishment plus one; (iv) enterprise debt ratio (DEBT), measured by the ratio of total debts to total assets; (v) enterprise industry (Industry), divided by two-digit SFC industry code; (vi) data year (Year), in order to separate the influence of enterprise size, profitability, establishment period, solvency, industry and year.

3.3. Regression Model Specification. In this study, the intensity of enterprise R&D investment is taken as the dependent variable. Market power and the nature of enterprise ownership are the moderating variables. Further, control variables such as enterprise asset scale, asset–liability ratio, profit margin, age of establishment, industry, and year are added to construct the regression model as follows:

$$\begin{aligned} RD_{i,t} &= \beta_0 + \beta_1 \mathrm{GOV}_{i,t} + \beta_2 \mathrm{SOE} + \delta_1 \mathrm{SOE}_{i,t} \times \mathrm{GOV}_{i,t} \\ &\quad + \beta_3 MS + \delta_2 MS \times \mathrm{GOV}_{i,t} + \beta_4 MC \\ &\quad + \delta_3 MC \times \mathrm{GOV}_{i,t} \\ &\quad + \varphi X_{i,t} + v_i + \varepsilon_{i,t}, \end{aligned} \tag{17}$$

where i is the enterprise, t is the year, β_0 is the constant term, GOV is the variable of government subsidy intensity, X is the corresponding control variable, V represents the individual unobservable effect, that is, the heterogeneity among enterprises, and $\varepsilon_{i,t}$ represents the random error term. In formula (17), MC and MS are respectively the proxy variables of the seller and buyer power of the enterprise, as stated above. This study defines market power from the perspective of buyer power and seller power. Therefore, in order to reveal in more depth the innovation subsidy effect of enterprises of different ownership under different market power combinations, this study divides the market power combinations into four different combinations according to the median of market power. At the same time, the enterprises in the sample data are divided into SOEs and non-SOEs, according to the differing ownership of enterprises. After the empirical regression, the regression results are compared and analyzed.

Table 1: Descriptive statistics of main variables.

Variables	Obs	Mean	SD	Median	Min	Max
RD	5697	0.05	0.04	0.037	0.000	0.627
GOV	5697	0.01	0.02	0.006	0.000	0.424
MS	5697	0.34	0.18	0.303	0.001	0.997
MC	5697	0.31	0.20	0.262	0.009	1.000
AGE	5697	16.57	5.30	16.000	1.000	58.000
SIZE	5697	7.58	1.05	7.516	4.248	12.186
PROFIT	5697	0.14	0.27	0.102	0.000	13.276
DEBT	5697	0.04	0.02	0.037	0.001	0.181
SOE	5697	0.24	0.43	0.000	0.000	1.000

4. Empirical Results and Analysis

4.1. Descriptive Statistics and Correlation Analysis. Table 1 shows descriptive statistics of the main variables used in this study. As can be seen from Table 1, the mean value of R&D investment intensity (RD) of enterprises is 0.05, which is relatively low, and the standard deviation is 0.040, indicating a relatively stable quality of the data. In general, China's listed manufacturing enterprises spend relatively less on R&D. However, the fact that some enterprises can spend 62.7% of their main business income on R&D shows that the intensity of R&D investment is very different across enterprises. The average value of government subsidy (GOV) is 0.01, which indicates that the intensity of government subsidy for listed manufacturing companies in China is still at a low level. It can be seen from the mean value of the enterprise ownership (SOE) variable that the number of non-SOEs in the sample data is relatively large, which is in line with the actual development of listed companies in China. The extreme values of MC and MS are also very different. Across the variation of market power, both buyer power and seller power have a maximum value close to 1, indicating that the top five suppliers or customers have absolute control over the enterprise, that is, the market power of these enterprises is relatively small. The variables adopted in this study have also passed correlation analysis, and the correlation coefficients between explanatory variables are all less than 0.5, which eliminates the estimation bias caused by multi-co-linearity between explanatory variables. The result of the correlation analysis is shown in Table 2.

4.2. Empirical Results and Analysis

4.2.1. Regression Results of Market Power, Enterprise Ownership, and R&D Subsidy Effect. Table 3 shows the regression results of market power, enterprise ownership, and R&D subsidy effect. The random effect model of panel data is adopted for model regression (according to the results of the Hausman test). Column (1) is mainly the regression result after adding all control variables, which serves as the reference for other models. On the basis of Column (1), the interaction term between government subsidies and enterprise ownership is added in Column (2), which is used to investigate the R&D investment of enterprises of different

Table 2: The result of correlation analysis.

	RD	GOV	MS	MC	lnAGE	Size	Profit	Debt	SOE
RD	1								
GOV	0.346*	1							
MS	−0.034	0.0129	1						
MC	0.082*	0.0427*	0.2050*	1					
lnAGE	−0.061*	−0.0566*	−0.0425*	−0.0393*	1				
Size	−0.217*	−0.1429*	−0.3302*	−0.1818*	0.1605*	1			
Profit	0.180*	0.1063*	0.0394*	0.0660*	−0.0176	−0.1450*	1		
Debt	−0.1883*	−0.0542*	−0.1192*	−0.00420	0.1011*	0.4008*	−0.0458*	1	
SOE	−0.0476*	0.0154	−0.0402*	0.0210	0.1578*	0.2891*	−0.0682*	0.2417*	1

Table 3: Regression results of market power, enterprise ownership, and R&D subsidy effect.

	(1)	(2)	(3)	(4)
GOV	0.295***	0.296***	0.295***	0.187**
	(0.061)	(0.081)	(0.082)	(0.112)
SOE	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
GOV#SOE		−0.003	−0.004	0.011
		(0.115)	(0.115)	(0.123)
MS			−0.011***	−0.010**
			(0.004)	(0.005)
MC			−0.002	−0.008**
			(0.004)	(0.005)
GOV#MS				−0.135
				(0.284)
GOV#MC				0.395*
				(0.242)
Age	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	−0.002***	−0.002***	−0.003***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Profit	0.010***	0.010***	0.010***	0.009***
	(0.004)	(0.004)	(0.005)	(0.005)
Debt	−0.086***	−0.086***	−0.089***	−0.086***
	(0.028)	(0.028)	(0.028)	(0.027)
_cons	0.019***	0.019***	0.028***	0.030***
	(0.008)	(0.007)	(0.008)	(0.008)
N	5697	5697	5697	5697
R^2	0.104	0.104	0.108	0.114
Wald chi2	859.99***	862.60***	883.39***	886.69***
Hausman test	139.91***	172.33***	174.64***	180.91***

Standard errors in parentheses; industry, location, and year are controlled in all models. $^{*}p < 0.15$, $^{**}p < 0.1$, $^{***}p < 0.05$.

ownership with different government subsidies. Column (3) adds market power on the basis of Column (2), and Column (4) adds the interaction term between government subsidies and market power on the basis of Column (3). As can be seen from Table 3, the regression coefficient of government subsidy intensity (GOV) is positive, and both are significant at the statistical level of 0.01. This result shows that the greater the level of government subsidies, the higher the intensity of enterprise R&D, that is, there is a certain crowding effect of government subsidies on enterprise R&D, which is consistent with most existing research findings on the effect of government subsidies in China.

The empirical regression results show that both buyer power and seller power are negatively correlated with enterprise R&D investment. The regression results of buyer power in Column (3) and Column (4) are significant, that is, the lower the total proportion of the top five suppliers of an enterprise, the greater the buyer power of an enterprise, and its R&D investment will increase: when an enterprise has a large buyer power, it is more likely to occupy a dominant position in the transaction process, thus reducing its negotiation cost, and thus allocating more energy and resources to the innovation stage to consolidate its market position. As can be seen from the regression results of Column (4), when the seller's market power is small, the effect of innovation subsidy is better. The smaller the seller's market power is (the larger the MC is), the more government subsidies are invested, which will lead to more R&D investment. This may be due to the fact that, with a small seller's market power, enterprises can better understand the needs of existing customers and increase R&D spending to better serve customers with the help of government subsidies. However, the regression coefficient between buyer power and government subsidies is not statistically significant. From the regression results of Column (2) to Column (4), the regression coefficients of enterprises of different ownership are not significant.

Next, in order to more deeply analyze the R&D subsidy effect of enterprises with different ownership in the face of different market power, this study divides different market power into groups and investigates the relationship between enterprise ownership and government subsidy effect under different combinations of market power.

4.2.2. Comparative Analysis of the Effect of Government Subsidies under Different Combinations of Market Power. In order to reveal the difference in innovation subsidy effect of enterprises with different ownership in the face of different market power combinations, this study divides the sample into four groups of different market power combinations based on the median of buyer power and seller power and performs regression on them one by one according to different ownership nature of enterprises. Specifically, we first calculate the medians of MS and MC to distinguish different market power. The median of MS is 0.3027 and the median of MC is 0.2617. Second, all enterprises are divided into SOEs and non-SOEs, according to

Table 4: Regression results of the influence of different market power combinations.

State-owned enterprise				Nonstate-owned enterprise			
Buyer	Large	0.287*** (0.040)	0.432*** (0.093)	Buyer	Large	0.196** (0.107)	0.287*** (0.082)
Power	Low	0.339 (0.250)	0.050 (0.072)	Power	Low	0.542*** (0.119)	0.075* (0.051)
		Low	Large			Low	Large
		Seller power				Seller power	

Table 5: Results of robustness checks.

State-owned enterprise				Non-state-owned enterprise			
Buyer	Large	0.286*** (0.050)	0.401*** (0.034)	Buyer	Large	0.212*** (0.065)	0.250*** (0.019)
Power	Low	0.289*** (0.084)	−0.027 (0.038)	Power	Low	0.405*** (0.037)	0.073*** (0.036)
		Low	Large			Low	Large
		Seller power				Seller power	

Standard errors in parentheses; industry, location, and year are controlled in all models. $^{*}p < 0.15$, $^{**}p < 0.1$, $^{***}p < 0.05$.

forms of ownership. For comparison, Table 4 only shows the regression coefficients of government subsidy intensity in each case.

The regression results in Table 4 show that, in the case of large buyer power, government subsidies will significantly promote the R&D investment of enterprises, regardless of whether they are SOEs or not. Such large buyer-power enterprises are generally large enterprises with core competitive advantages, and they have the capital and strength to compete with upstream enterprises. By taking advantage of such advantages, such enterprises can ensure their R&D investment and continue to invest in the innovation stage, thereby maintaining their leading position in the market competitive advantage. At the same time, the government continues to subsidize such enterprises, and this can send a positive signal to society and attract the attention of investors, thus ensuring the sustainable development of enterprises. This virtuous cycle of the innovation process is also expected by the government and society.

When both buyer power and seller power are low, the effect of innovation subsidy is significantly different among enterprises with different forms of ownership. For non-SOEs, government subsidies significantly promote R&D investment, but the effect of government subsidies on SOEs is uncertain. This is a topic that future research could explore. Enterprises with small seller power and buyer power are usually enterprises at a small scale, and non-SOEs among such enterprises are often faced with problems such as insufficient resources and insufficient innovation incentives. At this time, government subsidies can help these enterprises overcome capital constraints and increase their ability to resist risks.

SOEs face the opposite situation. Due to the defects of the system, small SOEs generally have shortcomings such as weak innovation and incomplete innovation incubation processes. Even if the government gives innovation subsidies, such enterprises are still prone to "living in the past" and are unable to attract and hire high-level technical talents, which leads to low innovation efficiency.

In cases where the seller has a large influence and the buyer has a small influence, the regression coefficient before the government subsidy (GOV) of the two types of enterprises is not significant. It is a task for the academic community to reveal the effect of different ownership on innovation subsidies under such market power. This is a problem worthy of discussion. However, it is beyond the scope of this study, and should be referred to in future research.

4.3. Robustness Checks. In this section, we test the robustness of our empirical results in this study. We performed several robustness tests by substituting independent variables, including control variables, and demonstrated the robustness of our results. To save space, we present one of these robust checks in Table 5 by controlling a firm-specific factor. From the regression results, the coefficient signs and significance of the variables investigated in this study, including government subsidy intensity, ownership, and market power, are basically consistent with the regression results in Table 4. The nature of SOEs is not certain in the two types of regression. In view of this, it may be necessary to exclude other types of enterprises for group regression, so as to obtain more conclusive conclusions. Meanwhile, the coefficient signs and significance of control variables such as enterprise age (AGE), enterprise size (SIZE), profit margin (PROFIT), and debt ratio (DEBT) are consistent with the results in Table 4, proving that our research results hold.

Endogeneity is also a matter of concern. There is a possible cause and effect between government subsidies and R&D investment. However, after many attempts, we have not found a suitable way to deal with the endogeneity problem in this study. There is also no mention of a feasible attempt in the relevant literature. Therefore, this also becomes an issue left for further research. Further explanation will be provided later if there is a suitable method to deal with the endogeneity problem in this study.

5. Conclusion and Discussion

Enterprises, upstream suppliers, and downstream customers are essential components of the contemporary marketing micro-environment. Every enterprise in the marketplace has complicated upstream and downstream industrial relationships. Government subsidy, as the "helping hand" of government, is an effective way to solve technological innovation and reduce innovation risk. In order to reveal the complex influence of market power and enterprise ownership on the effect of government innovation subsidy under the micro-environment of contemporary marketing, this study constructs a random effect model based on the sample data of Chinese listed manufacturing companies from 2009 to 2018. The empirical results show that there are great differences in subsidy effects of different ownership enterprises under different market power combinations. Specifically, in the case of large buyer power, government subsidy will significantly promote the R&D investment of enterprises, and this promotion effect has nothing to do with the ownership nature of enterprises. When both buyer power and seller power are small, government subsidies significantly promote R&D investment for nonstate-owned enterprises, but this effect is not significant for state-owned enterprises. In the case of large seller power and small buyer power, the effects of government subsidies on both state-owned and nonstate-owned enterprises are not significant. This is a question worthy of further discussion in future research.

The research contributions of this study are as follows. First, due to lack of data, most existing studies only study the impact of government subsidies on enterprise innovation in general and do not subdivide the effect of innovation subsidies on enterprises under different market power and different ownership. Considering that enterprises face both upstream and downstream enterprises in the market, each enterprise has two kinds of market power: seller power and buyer power. This study innovatively adopts the proportion of top five customers' total sales and the proportion of top five suppliers' total purchase as the proxy variables of seller power and buyer power, respectively. Based on the group investigation and comparative analysis of different market power and enterprise ownership, the study reveals in greater depth the effect of innovation subsidy when enterprises of different ownership face different market power. This study further opens up the theoretical black box of the relationship between government subsidies and enterprise innovation, which fills the theoretical gap in this aspect.

Second, the theory of industrial organization pays more attention to the problems of market power and enterprise innovation. Research on government subsidies and market power, however, seems to be split. The research on government subsidy mainly focuses on empirical analysis, while the research on market power mainly focuses on the derivation of a mathematical model. At the same time, the data used in existing studies are relatively old. Based on the transaction data published in the annual reports of Chinese listed companies from 2009 to 2018, this study examines the market power faced by enterprises, which not only provides empirical support for the relationship between market power and enterprise innovation but also provides relatively new empirical evidence for the empirical analysis of the effect of innovation subsidies.

Third, the empirical results show that there are significant differences in the effect of innovation subsidies for enterprises of different ownership under different types of market power. In the case of large buyer power, government subsidies will significantly promote the R&D investment of enterprises, regardless of whether or not they are SOEs. When both buyer power and seller power are low, the effect of innovation subsidy is significantly different among enterprises with different forms of ownership. For non-SOEs, government subsidies significantly promote R&D investment, but the effect of government subsidies on SOEs is not significant. This study provides an important theoretical point of reference for governments of developing countries seeking to implement innovation subsidy policies by classification. When formulating subsidy policies, the government should comprehensively consider the ownership nature of enterprises and the market environment of enterprises, and carry out targeted subsidies, so as to achieve "precise" subsidies.

5.1. Policy Implications. The policy implications of this study are as follows. First, given that government innovation subsidies are incentive based to a large extent, they should be further increased to encourage firms to actively engage in innovation activities. At the same time, the government should strengthen supervision and assessment to avoid information asymmetry between government and enterprises, so as to reduce the phenomenon where some enterprises pursue rent-seeking behavior and release false signals of innovation to misdirect government subsidies but do not then carry out R&D innovation.

Second, considering the positive impact of government subsidies on R&D investment of enterprises, when buyer power is large, the government should introduce the market competition mechanism in an orderly manner, gradually reduce the entry threshold of the upstream monopoly industry, and weaken the seller's market power of the upstream enterprises, thus increasing the buyer's counterweight power of the downstream enterprises, and promote the R&D investment of the downstream enterprises. Since the weakness of the seller power is not conducive to enterprise innovation, the government should introduce appropriate policies to encourage the formation of vertical innovation alliances between upstream and downstream enterprises, in order to eliminate the negative impact of the weakness of the seller's power.

Third, under the influence of market power, the effects of government innovation subsidies vary widely according to different forms of enterprise ownership. In view of this, the government should formulate different subsidy policies for enterprises with different forms of ownership. The direction of government subsidies should be further adjusted to appropriately reduce subsidies to large, well-funded SOEs, in favor of private enterprises that are highly motivated to innovate and more in need of R&D funding supplements. Non-SOEs should be guided toward making "long-term" R&D decisions. The policy focus should be to reduce the uncertainty and risk of innovation, to continuously cultivate and accumulate R&D capabilities, and to improve their competitive advantages. As previous studies point out, the R&D input of SOEs is higher than that of other types of enterprises, but their R&D output is relatively poor. Therefore, for SOEs, corresponding technological development goals should be formulated to promote the optimization of the R&D input–output ratio guided by innovation output.

5.2. Limitations and Future Directions. This study investigates the effect of government innovation subsidy under different market power and different ownership, but there remain limitations. Future research can be carried out from the following aspects. First, it is necessary to further differentiate the methods of government subsidies. Government subsidies can be divided into presubsidy and postsubsidy, R&D subsidy and non-R&D subsidy, so as to further investigate the response of enterprises of different ownership to government subsidies in different ways under market power.

Second, since 2009, the China Securities Regulatory Commission (CSRC) has required listed companies to disclose the transaction shares of the top five upstream and downstream trading partners of enterprises, which has provided a more reliable data source for this study to investigate the buyer power and seller power. However, many listed companies do not disclose the names of upstream and downstream enterprises in their data disclosure. With more standardized data disclosure of listed companies in China, some new methods to measure market power can be introduced into the approach in this study.

Third, this study uses manufacturing enterprises in the database of listed companies as samples, because these enterprises are much more likely to receive government subsidies than nonlisted enterprises. However, the number of nonlisted companies subsidized by the government still accounts for the majority, which may lead to sample selection problems in studies that only select listed companies as samples. At the same time, after more industrial enterprises are taken into account, the measurement of upstream and downstream market power of manufacturing enterprises will be more accurate. However, the existing database of Chinese industrial enterprises is relatively poor in the data quality of government subsidies, upstream and downstream market power, etc. With the continuous opening and improvement of this database or related databases, the relevant conclusions of this study can be further tested.

Data Availability

After the publication of this study, data are available upon request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest or personal relationships that could have appeared to influence the work reported in this study.

Acknowledgments

This work was supported by National Natural Science Fund of China (Grant no. 72102090), Humanities and Social Science Project of Ministry of Education (Grant no. 21YJC630112) and the National Social Science Fund of China (Grant no. 21BTJ).

References

[1] K. J. Arrow, "Economic welfare and the allocation of resources to invention," in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, R. R. Nelson, Ed., pp. 609–626, Princeton University Press, Princeton, NJ, USA, 1962.
[2] G. Tassey, "Policy issues for R&D investment in a knowledge-based economy," *The Journal of Technology Transfer*, vol. 29, no. 2, pp. 153–185, 2004.
[3] J. E. Stiglitz and A. Weiss, "Credit rationing in markets with imperfect information," *The American Economic Review*, vol. 71, no. 3, pp. 393–410, 1981.
[4] B. Aschhoff, *The Effect of Subsidies on R&D Investment and Success: Do Subsidy History and Size Matter?*, ZEW-Centre for European Economic Research Discussion, 2009.
[5] J. Warda, "Measuring the value of R&D tax provisions," in *OECD. Fiscal Measures to Promote R&D and Innovation*pp. 9–22, Paris, 1996.
[6] B. S. Tether, "Who co-operates for innovation, and why," *Research Policy*, vol. 31, no. 6, pp. 947–967, 2002.
[7] R. Kleer, "Government R&D subsidies as A signal for private investors," *Research Policy*, vol. 39, no. 10, pp. 1361–1374, 2010.
[8] L. Yager and R. Schmidt, *The Advanced Technology Program: A Case Study in Federal Technology Policy*, pp. 15–18, AEI Press, Washington, DC, USA, 1997.
[9] S. Martin, "R&D joint ventures and tacit product market collusion," *European Journal of Political Economy*, vol. 11, no. 4, pp. 733–741, 1996.
[10] I. Busom, "An empirical evaluation of the effects of R&D subsidies," *Economics of Innovation and New Technology*, vol. 9, no. 2, pp. 111–148, 2000.
[11] S. J. Wallsten, "The effects of government-industry R&D programs on private R&D: the case of the small business innovation research program," *The RAND Journal of Economics*, vol. 31, no. 1, pp. 82–100, 2000.
[12] P. Boeing, "The allocation and effectiveness of China's R&D subsidies - evidence from listed firms," *Research Policy*, vol. 45, no. 9, pp. 1774–1789, 2016.
[13] M. Marino, S. Lhuillery, P. Parrotta, and D. Sala, "Additionality or crowding-out? An overall evaluation of public R&D subsidy on private R&D expenditure," *Research Policy*, vol. 45, no. 9, pp. 1715–1730, 2016.
[14] J. V. Blanes and I. Busom, "Who participates in R&D subsidy programs? The case of Spanish manufacturing firms," *Research Policy*, vol. 33, no. 10, pp. 1459–1476, 2004.
[15] R. E. Hoskisson, M. Wright, I. Filatotchev, and M. W. Peng, "Emerging multinationals from mid-range economies: the

influence of institutions and factor markets," *Journal of Management Studies*, vol. 50, no. 7, pp. 1295–1321, 2013.

[16] J. Á. Zúñiga-Vicente, C. Alonso-Borrego, F. J. Forcadell, and J. I. Galán, "Assessing the effect of public subsidies on firm R&D investment: a survey," *Journal of Economic Surveys*, vol. 28, no. 1, pp. 36–67, 2012.

[17] R. Tamaschke, G. Docwra, and R. Stillman, "Measuring market power in electricity generation: a long-term perspective using a programming model," *Using a Programming Model . Energy Economics*, vol. 27, no. 2, pp. 317–335, 2005.

[18] M. A. Bellamy, S. Ghosh, and M. Hora, "The influence of supply network structure on firm innovation," *Journal of Operations Management*, vol. 32, no. 6, pp. 357–373, 2014.

[19] C. M. Christensen and J. L. Bower, "Customer power, strategic investment, and the failure of leading firms," *Strategic Management Journal*, vol. 17, no. 3, pp. 197–218, 1996.

[20] R. Henderson and I. Cockburn, "Scale, scope, and spillovers: the determinants of research productivity in drug discovery," *The RAND Journal of Economics*, vol. 27, no. 1, pp. 32–59, 1996.

[21] J. Peters, "Buyer market power and innovative activities," *Review of Industrial Organization*, vol. 16, no. 1, pp. 13–38, 2000.

[22] R. Inderst and C. Wey, "Buyer power and supplier incentives," *European Economic Review*, vol. 51, no. 3, pp. 647–667, 2007.

[23] Z. Chen, "Supplier innovation in the presence of buyer power," *International Economic Review*, vol. 60, no. 1, pp. 329–353, 2019.

[24] P. Yu, J. Shi, B. M. Sadowski, and Ö. Nomaler, "Catching up in the face of technological discontinuity: exploring the role of demand structure and technological regimes in the transition from 2G to 3G in China," *Journal of Evolutionary Economics*, vol. 30, no. 3, pp. 815–841, 2020.

[25] J. Child and D. K. Tse, "China's transition and its implications for international business," *Journal of International Business Studies*, vol. 32, no. 1, pp. 5–21, 2001.

[26] X. Liang, X. Lu, and L. Wang, "Outward internationalization of private enterprises in China: the effect of competitive advantages and disadvantages compared to home market rivals," *Journal of World Business*, vol. 47, no. 1, pp. 134–144, 2012.

[27] L. Luo, Y. Yang, Y. Luo, and C. Liu, "Export, subsidy and innovation: China's state-owned enterprises versus privately-owned enterprises," *Economic and Political Studies*, vol. 4, no. 2, pp. 137–155, 2016.

[28] J. Dai, X. Li, and H. Cai, "Market power, scale economy and productivity: the case of China's food and tobacco industry," *China Agricultural Economic Review*, vol. 10, no. 2, pp. 313–322, 2018.

[29] X. H. Sun, X. Guo, and J. Wang, "Government subsidy, ownership and firms' R&D decisions," *Journal of Management Sciences in China*, vol. 20, no. 6, pp. 18–31, 2017, in Chinese.

[30] A. Guangzhou Hu, "Ownership, government R&D, private R&D, and productivity in Chinese industry," *Journal of Comparative Economics*, vol. 29, no. 1, pp. 136–157, 2001.

[31] C. Lin, P. Lin, and F. Song, "Property rights protection and corporate R&D: evidence from China," *Journal of Development Economics*, vol. 93, no. 1, pp. 49–62, 2010.

[32] X. González and C. Pazó, "Firms' R&D dilemma: to undertake or not to undertake R&D," *Applied Economics Letters*, vol. 11, no. 1, pp. 55–59, 2004.

[33] A. K. Dixit and J. E. Stiglitz, "Monopolistic competition and optimum product diversity," *The American Economic Review*, vol. 67, no. 3, pp. 297–308, 1977.

Hindawi
Complexity
Volume 2022, Article ID 4641932, 10 pages
https://doi.org/10.1155/2022/4641932

WILEY | Hindawi

Research Article

Applying Noise-Based Reverse Correlation to Relate Consumer Perception to Product Complex Form Features

Jose Antonio Diego-Mas,[1] **Jorge Alcaide-Marzal**,[1] **and Rocio Poveda-Bautista**[2]

[1]*Institute for Research and Innovation in Bioengineering (i3B), Universitat Politècnica de València, Camino de Vera s/n, Valencia 46022, Spain*
[2]*Institute of Innovation and Knowledge Management (INGENIO) (CSIC-UPV), Universitat Politècnica de València, Valencia 46022, Spain*

Correspondence should be addressed to Jose Antonio Diego-Mas; jodiemas@dpi.upv.es

Received 18 May 2022; Revised 27 June 2022; Accepted 9 July 2022; Published 16 August 2022

Academic Editor: Ning (Chris) Chen

Consumer behavior knowledge is essential to designing successful products. However, measuring subjective perceptions affecting this behavior is a complex issue that depends on many factors. Identifying visual cues elicited by the product's appearance is key in many cases. Marketing research on this topic has produced different approaches to the question. This paper proposes the use of Noise-Based Reverse Correlation techniques in the identification of product form features carrying a particular semantic message. This technique has been successfully utilized in social sciences to obtain prototypical images of faces representing social stereotypes from different judgements. In this work, an exploratory study on subcompact cars is performed by applying Noise-Based Reverse Correlation to identify relevant form features conveying a sports car image. The results provide meaningful information about the car attributes involved in communicating this idea, thus validating the use of the technique in this particular case. More research is needed to generalize and adapt Noise-Based Reverse Correlation procedures to different product scenarios and semantic concepts.

1. Introduction

Knowledge about customer requirements is essential to developing successful products [1, 2]. Moreover, in marketing research, product aesthetics is considered a key factor to the affective response and purchase intention of consumers [3–8]. Scholars have studied for long the complex relationship between the visual appearance of an object and the elicited consumer response. As a result, a variety of models have been proposed to explain the consumer affective response (CAR) to product design, either generic ones, such as the Unified Model of Aesthetics [9], or directly actionable such as Kansei Engineering [10, 11]. The modeling of this consumer behavior is a complex problem due to two main reasons. The first one is the difficulty of measuring subjective judgements [1]. The second one is that products need to be parameterized, it is, described in terms of shape characteristics (product form features, PFF), to find relationships between them and the consumer response. These parameterized models must reflect the complexity of the product visual representation using a limited number of variables to make their use feasible. Therefore, from a marketing perspective, it is essential to detect the most relevant product features to evaluate their influence on consumer perception [12].

The problem of parameterization is also present in some psychological and social sciences experiments; for example, those focused on studying prototypical images of social stereotypes. In these cases, indirect approaches such as Reverse Correlation (RC) are used to overcome the problem. RC operates by presenting random variations of stimuli of the object under study (pictures of faces, in most cases) with no prior assumptions, leaving the participants the task of making the most meaningful attributes emerge through their responses to a given judgement [13]. RC studies produce a Classification Image (CI), which is considered to represent a mental image of the prototypical object the participants were asked about.

In this study, we propose applying the same approach to the case of product perception. In particular, we analyze the application of a RC technique, the Noise-based Reverse Correlation (NBRC), to the identification of the aesthetic features of a product that contribute to convey a desired affective concept, through the determination of the CI for that product-concept pair. To assess the viability of this approach, we performed an exploratory experiment using sports cars as the object of study.

1.1. The Relevance of the Aesthetic Factor in Marketing Research. The visual appearance of consumer products plays a crucial role as a marketing differentiation factor, especially in highly saturated consumer markets [3–7]. The image is the first information channel in the consumer-product interaction [14], and consequently, aesthetics becomes a key factor in the product judgement by consumers [15–17]. It has been shown, for instance, that products with higher hedonic qualities are more appealing [18]. An in-depth analysis of these complex aspects of user-product interaction is carried out in [19].

Due to this reason, the influence of the visual appearance of products has been studied for long [8, 20–22], even in terms of purchase experience design [23]. However, knowledge about how users perceive a given product cannot be implemented through design without knowing why it is perceived this way. Thus, much research has focused on the relationship between this consumer perceptual response and the design parameters of the product, as they are the objective features that the designer can control [24, 25].

For instance, Kansei Engineering [10, 12] and Conjoint Analysis [26, 27] constitute two effective tools to find relationships between consumer response and product visual features. However, several factors are difficult in their use in a more general approach. For example, it is necessary to preestablish the formal characteristics of the product in order to use these tools. Product parameterization is needed in advance to obtain results. Then, the utility of these results depends on the ability of researchers to select product features relevant to the consumer affective response [12]. Moreover, these features are often broadly described to simplify the product description, thus limiting the ability of these techniques to capture the influence of specific design details [28]. Techniques such as eye-tracking [29] have been used to overcome these limitations.

This paper proposes an alternative approach to overcome the problem of detecting product features meaningful to consumer perception. It consists of using the RC technique, described in the next section, to obtain a "prototypical image," an image containing the visual features of an object that convey a specific message. This image may provide the designer with information useful to communicate this concept through the product's appearance. This information is especially interesting as typicality is a relevant factor in consumer' judgement. It has been shown that typicality influences the consumer response to a product [30]. The identification of "prototypical features," product form features highly contributing to the whole perception of the prototypical product, would allow designing with sound criteria to control to which extent the image of the product is conveying typicality in the desired concept.

RC methods have an extensive application in psychosocial studies, but no research has been found to be applied to product design. We explore in this work the feasibility of using RC techniques to obtain the prototypical image of a product representing an aesthetic/affective concept. The next section is devoted to explaining this technique thoroughly.

1.2. The Reverse Correlation Methods. People generally agree in their judgements of the aesthetic of consumer products. Therefore, there must be a relationship between the stimulus (the product) and the response (the perception). Several methods have been used to model this complex relationship. Direct approaches use sets of stimuli built by varying the values of the attributes which define the product (product form features, PFF) to produce different responses. These responses are then correlated to the stimuli to determine the relationship model. However, using this approach will produce larger experiment designs as the number of defining attributes and their possible values increase. This is the case of most consumer products, which need many attributes to get their form fully defined. In these situations, it might be preferable to use a different approach, such as RC [31, 32], to develop this type of stimulus-response model.

In direct methods, the relevant attributes of the stimulus are fixed, and their values are systematically manipulated and correlated to the responses. In RC methods, it is the opposite. The relevant attributes of the stimulus are not fixed, while the response variable is. Each stimulus is randomly generated, and the obtained responses are used to classify each input regarding the judgement. Due to this, these techniques are called "reverse," as the information about the influence of the attributes on the judgement is obtained by correlating the presented stimuli with the given responses. RC is a data-driven technique that does not need priory suppositions about the relevant attributes of the stimulus and permits the participant to use the criteria they want to judge the stimuli [32, 33].

2. Materials and Methods

The procedure for conduct a RC experiment is based on the use of a base stimulus, which is randomly modified, generating many samples for a survey. Participants are asked to judge them, and the CI is derived from their answers. There are different variations of this basic approach [34]. One of them is NBRC, often used to obtain mental representations [33]. In recent years, NBRC procedures have been mainly used in face perception research [32, 33, 35–40]. When we see a face for the first time, we infer the personality traits of that person by matching the visual input to our mental prototypes of faces with different attributes. From the result of this match, we infer the personality traits of the owner of the face [38], making attributions such as trustworthiness or dominance [41–46]. NBRC methods produce relevant CIs displaying the image that the participants use as a referent to evaluate the required judgement, referred to as "prototypical image" [33]. Following the same approach in this work, the NBRC method was used to obtain the prototypical image of a consumer product. As far as we know, this work is the first study applying this approach to product design.

The NBRC technique uses a starting base face to generate many variations by applying random noise layers over it. Usually, this base image is not an actual one but a composition of different greyscale images in which the face contour is made coincident and subsequently blurred. The base face features (gender, age, expression) are selected according to the requirements of the study. Once the base face is obtained, variations are generated applying different types of noise over it. The most usual ones are sinusoidal noise, white noise, or Gabor noise [32, 40, 47].

A survey is then prepared using these images. It consists of around 300/1000 tasks per participant, and in each one, a pair of pictures is shown. One of them is the base image with a noise pattern applied. The other one uses the same base image, but the noise pattern is inverted. The participants must select one of them for each task. The CI is created by averaging all noise patterns of the chosen pictures. When this average pattern is applied over the base face, the resulting image displays the traits that induced the judgement under study. In other words, this image represents a face conveying this particular social judgement (prototypical face). According to [32], the image obtained by applying the average pattern from nonselected pictures in the survey (the anti-CI) would display the inverse of the prototypical face.

Our intention in this work was to check if the NBRC could be used to visualize mental representations of products that fit some target judgement in the same way that it does for faces. Perceiving faces is a critical task for humans, and, to meet this need, after millions of years of evolution, our brain developed complex specialized neural networks intended to perceive faces [48]. For this reason, faces are perceived in a different way from other kinds of objects [49–51]. Human observers perceive faces in some objects that resemble the shape of a human face, such as a clock or the front of a car. Facial perception research has studied this effect extensively, known as pareidolia.

Several works found similarities between the neural activity of observers during the perception of faces and those registered when an object that resembles the shape of a face is perceived [52–55]. The front end of a car is one of the best examples of anthropomorphization in the perception of consumer products [56]. Cars can be classified using many criteria. One of the most common and well-known taxonomies is the sports car versus the family car, and the difference between these kinds of cars can be clearly seen on the front end of the cars. Therefore, in this first attempt to obtain the prototypical image of a consumer product using NBRC, we selected the frontal view of a car as the product and the appearance of a sports car as the fitting judgement.

3. Case Study

Sports cars were used as a case study to test the applicability of NBRC to relate consumer perception to complex product form features. We perform the task following the procedure depicted in Figure 1, which consists of 5 steps detailed in the following sections.

3.1. Stimuli and Participants. Randomly varied images of cars were created, overlaying different random noise patterns over a base image (Figure 1 (A)). The base image is obtained by averaging grayscale images of the object analyzed (typically a face), which leads to base images with blurry contours. To create our base image of a front end of a car, frontal images of six subcompact cars (B-segment) were selected. The images were converted to grayscale, cropped, and centered to get the area of the cars to span as a large part of the image as possible. The six images were overlaid using different transparency values, finally obtaining the base car image (Figure 2).

In this work, we used sinusoidal noise [32, 40] to generate the stimuli because it generated more meaningful variations of the base car than other commonly used types of noise such as white [57, 58] or Gabor noise [47]. To use sinusoidal noise in this task, the image height and width must be equal and have a power of 2. Therefore, the resulting image was resized to 512×512 pixels. The rcicr R package [59] was used to generate the stimuli. Firstly, 300 sinusoidal noise patterns were created by combining five layers of sinusoidal patches. The five images differ in the spatial frequency of the sinusoids (2, 4, 8, 16, and 32 cycles per image). In the same way, each one of these images was obtained by averaging twelve sinusoidal patches that differ in orientation and phase (6 different orientations and two phases) and in the contrast of the image, that was randomly assigned. Lastly, a final pool of 600 paired images was obtained by inverting each noise pattern. This complete noise generation process is shown in [32]. Finally, each noise pattern pair was superimposed on the base car image, obtaining 300 slightly different pairs of stimuli. Figure 2 shows the base car image and one stimuli pair obtained following this process.

25 Spanish young adults (65% men and 35% women) between 24 and 35 years old ($M = 27.40$, $SD = 3.67$) participated in the experiment [60], which was approved by the ethics committee at the Universitat Politecnica de Valencia (P15_10_01_20). Individual consent forms were also gathered.

3.2. Survey Procedure. The survey consisted of two blocks of 150 tasks. Each one presented a pair of pictures (direct and inverse noise layers) side-by-side (Figure 3). The participants were asked to quickly choose in each task the car they reckoned as having a sports car appearance at first impression, insisting on this point despite the understandable difficulty of the task.

The participants were shown both the stimuli pairs and the position of direct and inverse pictures randomly. They had to select one of the stimuli by clicking the corresponding

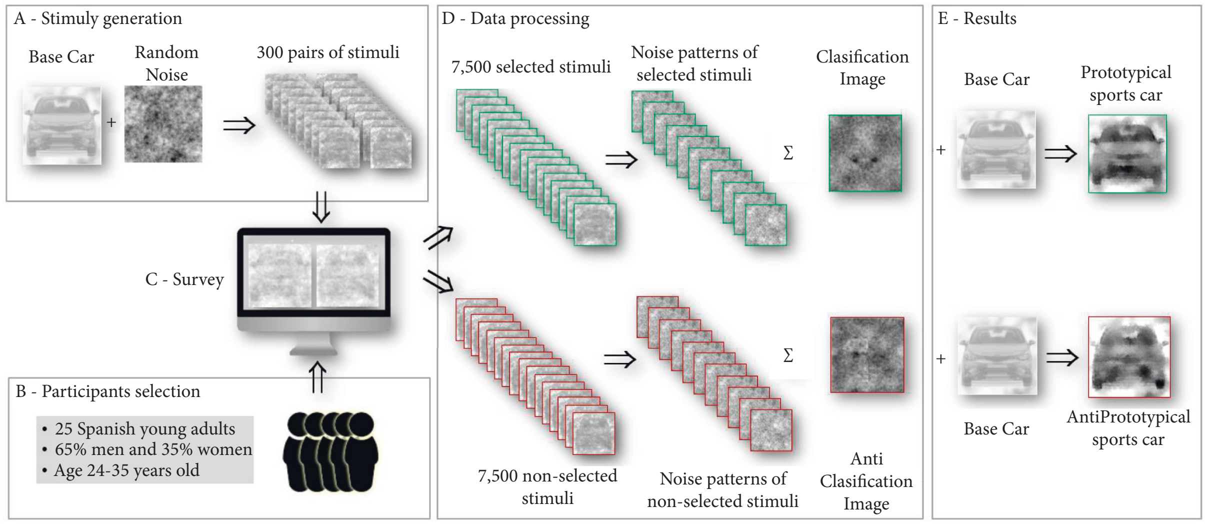


Figure 1: Five steps of the NBRC task to obtain the prototypical and antiprototypical images of a sports car.

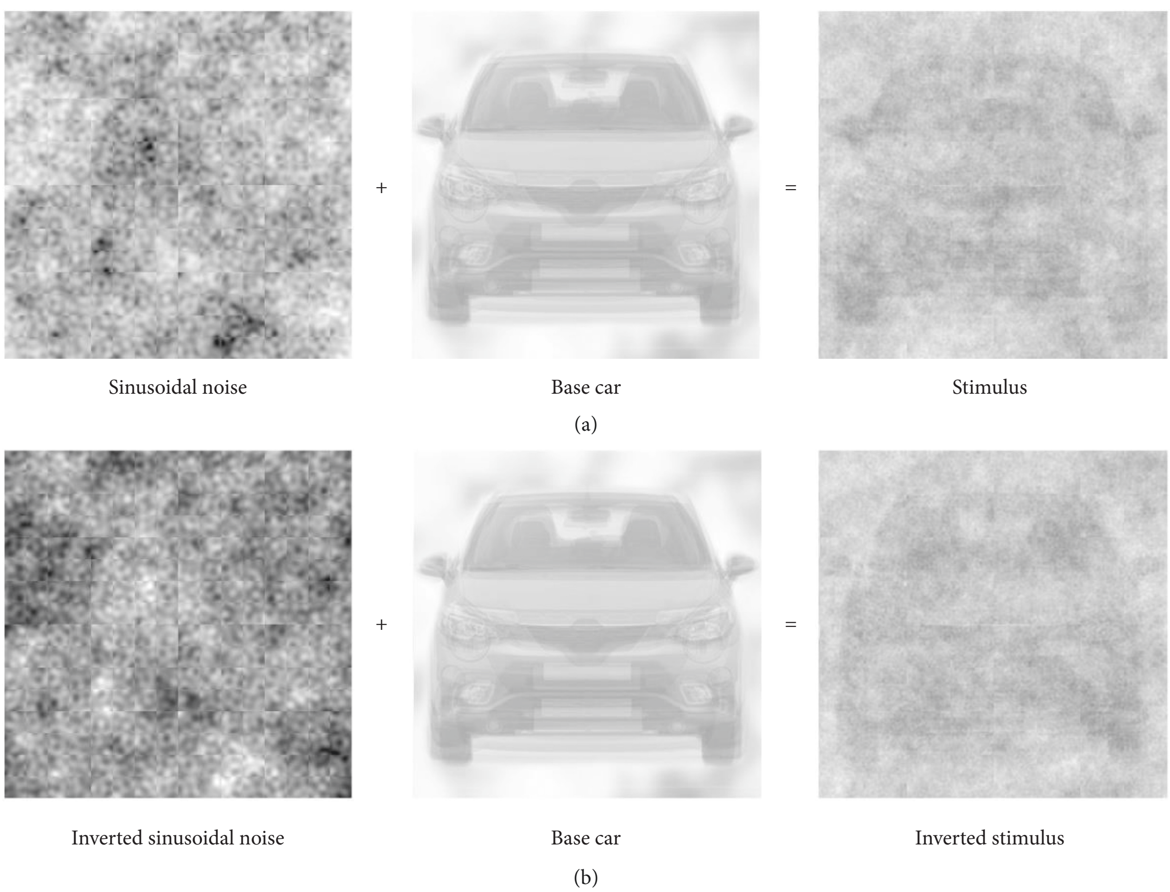


Figure 2: Sinusoidal noise is applied to the base image to obtain a stimulus (a). The inverted stimulus is obtained by applying the inverted noise to the base image (b).

button under the stimuli (see Figure 3) or by pressing the left/right arrow key.

3.3. Data Processing. After the survey, a CI per participant was obtained by averaging the noise patterns of the chosen pictures and, similarly, an anti-CI was produced using the noise patterns of the unselected ones. A total of 7,500 answers were processed, with the average response time by trial across all participants being 3.67 seconds. The *rcicr* R package (v. 0.3.4.1) was used for this task [59]. According to [32], the CI and anti-CI represent the extreme images in the individual judgement scale (an image displaying the visual

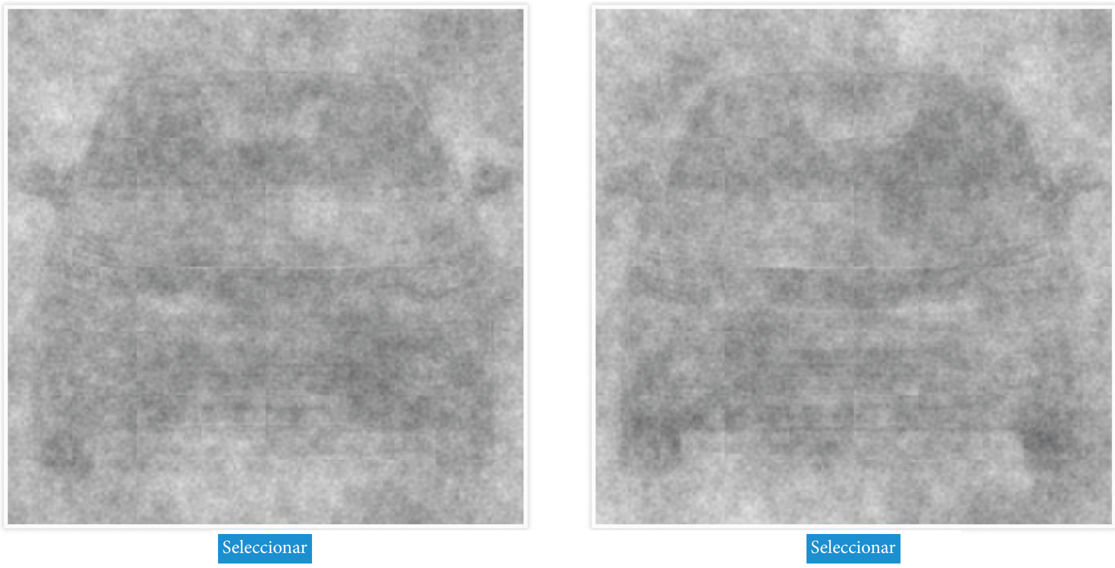


FIGURE 3: Stimuli pair presented to participants in one trial.

features of a sports car and another one showing what is not considered a sports car). Finally, the average CI and anti-CI for all participants were generated by averaging the noise pattern of the individual CIs and anti-CIs (Figure 1 (D)).

4. Results

The individual CIs and anti-CIs of each participant were overlaid on the base image (Figure 1 (E)). S1 Table in the Supplementary Material of this paper shows all the 50 images. As an example, Figure 4(a) shows the images obtained for participant 3. To increase the visibility of the results, a selective Gaussian Blur filter (radius = 30; max delta = 10) and a shadow/highlight compensation filter were applied, resulting in the images in Figure 4(b). The global CI and anti-CI images in Figure 5 were obtained by overlaying the average CI and anti-CI for all the participants on the base car, while Figure 5(b) shows the filtered version of the global CIs.

To show which parts of the image were most relevant to convey the sports/nonsports appearance, we used *rcicr* to prepare a z-map (Figure 6) using a Gaussian filter of radius 5, a background mask and applying a z-transform over the luminance of the CIs noise pixels [32]. Green zones in this representation correspond to areas of the image that directly convey the sports car look, while the red and white zones provoke the inverse response (nonsports car).

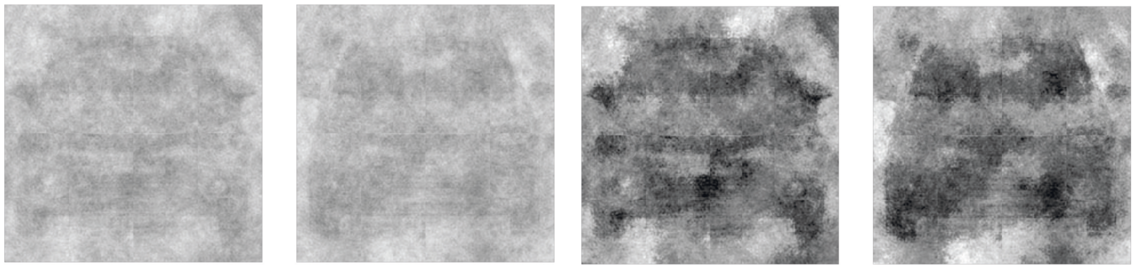
5. Discussion

In this work, we have proposed the use of RC, a technique used in social research, to the identification of product visual features relevant to eliciting a particular consumer response. To explore the viability of this approach, a case study has been conducted.

Due to the exploratory nature of this work, cars were selected as the object of study to facilitate the generation of a distinguishable CI. Cars are products of very widespread use and they display easily interpretable visual attributes. NBCR has proved to be a successful tool in the face perception field [61] and the front end of a car resembles the shape of a face, being one of the best examples of anthropomorphizing in the perception of consumer products [56]. In addition, sports cars are generally recognizable by many people, and their stereotype features are easy to forecast. Therefore, we could contrast if the resulting CI depicted some of the main characteristics typical of this kind of product.

According to this, the results of the experiment are satisfactory and the image obtained can be related to that of a sports car in several of its visual features. It is true that, as expected, individual CIs (Figure 4) are difficult to interpret. However, the addition of the information contained in the noise of all individual CIs leads to a clearer pattern, and some features typically related to a sports car can be identified in the global CI (Figure 5(a)) while they are not present in the global anti-CI (Figure 5(b)). In this regard, it should be noted that the base image used in an NBRC task significantly influences and limits the space of attainable results. The information sampled in the noise patterns of the CIs cannot deeply change the base image. We created our base image using frontal images of six subcompact cars out of the typical sports car segment. Therefore, slight changes in the form and details increasing the sportiness perception of the base car were expected, rather than major changes to the main dimensions or basic shapes that would transform a subcompact car into a typical sports car. Despite this, interestingly, a modification of the ratio height-width can be perceived in the CI.

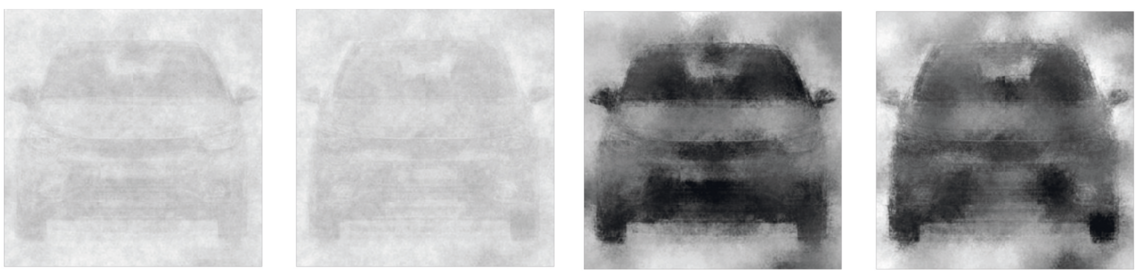
Moreover, comparing the global CI image with the global anti-CI and the base image, some differences can be noticed (Figure 5). The vehicle in the global CI seems lower and presents a slight increase in the width of the front from the anti-CI. There are differences in the headlights area, giving a more aggressive impression on the global CI due to



Subject 3 CI | Subject 3 Anti-CI | Subject 3 filtered CI | Subject 3 filtered Anti-CI

(a) (b)

Figure 4: (a) Individual CI and anti-CI of subject 3 and (b) individual CI and anti-CI of subject 3 after the blur and shadow/highlight compensation filters were applied.



Global CI | Global Anti-CI | Global filtered CI | Global filtered Anti-CI

(a) (b)

Figure 5: (a) Global CI and anti-CI and (b) global CI and anti-CI after the blur and shadow/highlight compensation filters were applied.

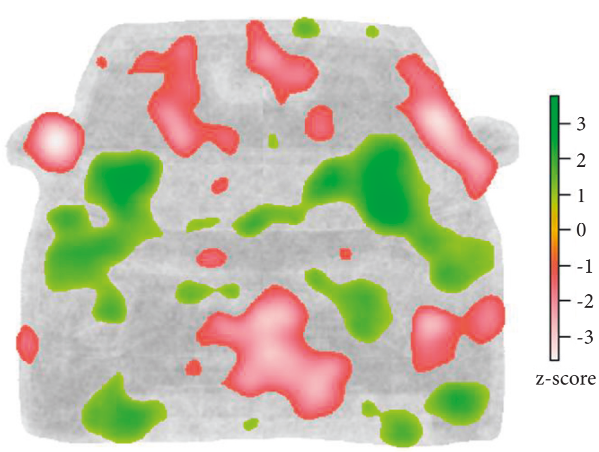


Figure 6: Z-map of the CI. Areas eliciting sports car perception are displayed in green, while those conveying the inverse perception are displayed in red and white.

its bigger size and curvature. The front bonnet looks different on both cars. The bonnet appears dark in the center and clearer on the sides in the CI, while the anti-CI presents the opposite pattern. This conveys the impression of the presence of elevated feature lines near the bonnet boundary in the CI. In the anti-CI, the bonnet seems to be a rounded continuous metal sheet, as in the CI, it looks like a more complex concave/convex surface. Finally, the CI has the appearance of having longer side-view mirrors and shorter ground clearance. All these individual features are common characteristics of sports vehicles and, in general, the car in the CI conveys the impression of a sports car to a greater extent than the car in the anti-CI. Therefore, we could conclude that the technique has performed successfully in this particular case.

These subjective impressions are compatible with the results of the cluster test performed on the noise data of the CIs (Figure 6). The resulting z-map shows the parts of the car that significantly influence the stimuli classification (green, red, and white zones). It can be seen how, in general, the elements of the car mentioned above fall into these areas. The luminance of the pixels in the bonnet and headlight areas of the car shows that these parts have a great influence on the sportiness perception, while those in the lateral rear mirror area do the same but correlate inversely. The features related to structural changes (for example, changes in the apparent height, width, or ground clearance of the car) are more difficult to detect in the z-map. However, the green zone between the car underbody and the ground can be related to the shorter ground clearance appearance of the car in the CI than that in the anti-CI.

As aforementioned, assessing consumer perception is a complex process. However, the results of this study have been satisfactory and the NBRC can be considered a promising marketing tool in the field of product design. The obtained global CI reflects, at different grades, several of the features expected. Some of these features are easily noticeable, such as the bonnet line, the headlights, or the lateral

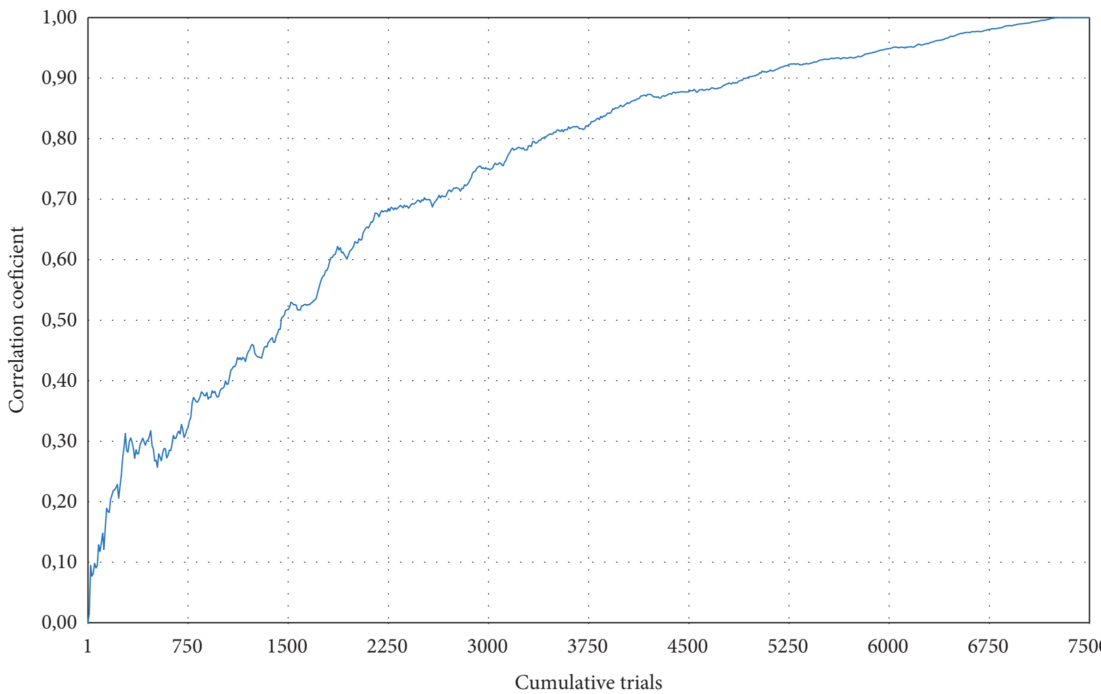


Figure 7: Correlation between cumulative CI and final CI.

rear mirrors. It is worth noting that the arising of these features is strongly restricted by the original car typology. RC studies have by their very nature this kind of limitation and the resulting CI is heavily dependent on the stimuli utilized [33]. Thus, the obtained prototypical image should be considered that of a subcompact sports car. This is something to consider when dealing with specific marketing goals (for example, when assessing sustainable or socially responsible product features).

We must also consider that RC works very efficiently with subtleties affecting facial features, but major changes in product structure are presumably harder to show up. As said above, in the present experiment, some of these structural variations were partially observed, such as changes in the appearance of the whole car proportions, which is very promising. An interesting future research field aims at studying if other kinds of products are less variable in shape but not in surface details (shoes, helmets, packaging). This factor is not so relevant and RC proves more powerful.

However, some limitations in this study must be pointed out. Every participant performed 300 trials in the NBRC task. The selection of this number was based on the face perception research literature using NBRC [62]. While increasing the number of trials by respondent would lead to more detailed CIs, the demotivation of the participants would also increase, raising the probability of random responding. Regarding the number of respondents, 25 participants took part in the NBRC task. Previous works in face perception research obtained well-defined CIs using between 20 and 30 participants [32, 39, 63].

Therefore, although 300 trials and 25 participants seem to be optimal in face perception, more research is needed to establish these values in the application of NBRC in the field of marketing. Generally, product research intends to gather meaningful information about at least market segment sizes, so the CI should account for a significant number of individuals. Moreover, focusing on more specific products and judgements would require appropriately dimensioning the sample from a demographic point of view.

On the contrary, fewer trials may suffice if the shape of the analyzed product is simple, without small features, and with limited relevant details. The global CI obtained in this work is the result of the analysis of 7500 trials. Figure 7 shows how the number of trials affects the information gathered by the noise pattern of the final global CI. This graph represents the Pearson correlation coefficient between the luminance of the pixels of the final global CI and those in CIs obtained using fewer trials. To get these data, we varied the number of trials used to generate CI from 10 to 7500 (step-size = 10). As can be seen in Figure 7, the correlation between the cumulative CI and the final CI reaches 0.82 when half part of the available trials are used.

In any case, it is not possible to generalize the results obtained until more research is performed. As aforementioned, the product chosen is widespread and the prototypical image should supposedly be solid. In this sense, it is necessary to conduct more studies with different kinds of products to study the suitability of this technique with less familiar examples. Given the small number of existing studies using this approach outside face perception research, there is still a lack of information on how the base image used during the survey can influence its outcome. More experiments with different types of products would be required to contrast the validity of the method and to build a solid methodology. It is assumed that objects with a less generic shape or with a wider visual variability will require specific graphic treatment of the base images used. On the other hand, we have already pointed out that there is some similarity between the way in which our brain processes facial information and that in which we perceive objects that resemble faces [52–55]. More studies are needed using less anthropomorphic products to check if the NBRC performs equally when the pareidolia effect does not occur.

Our future work will address these issues and explore other possibilities. It might be interesting to contrast the results obtained through NBRC with those from other user-product interaction assessment techniques such as Kansei Engineering or to contrast the z-maps obtained by NBRC with those produced using eye-tracking for the same product/judgement pair.

6. Conclusions

This work presents a proposal of the use of Noise-Based Reverse Correlation for product perception assessment. This is, to our knowledge, the first application of this technique to product analysis. The results obtained are satisfactory and promising: The CI produced in the exploratory study portrays some of the expected features of a sports car, thus validating this particular case.

However, as we have described, the product was chosen to meet certain requirements in order to intuitively facilitate the application of RC. Therefore, despite the favorable results of this study, similar experiments in other different cases are needed to be able to generalize the suitability of the application of this technique in marketing research.

Data Availability

The image data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Supplementary Materials

Individual Classification and Anti-Classification Images by experimental subject are shown in Table S1 in the Supplementary Materials file of this paper. (*Supplementary Materials*)

References

[1] J. Arenas-Gaitán and B. Sanz-Altamira, "Complexity of understanding consumer behavior from the marketing perspective," *Complexity*, vol. 2019, Article ID 2837938, 3 pages, 2019.

[2] Y. Zhang, A. Wang, and W. Hu, "Deep learning-based consumer behavior analysis and application research," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 2837938, 7 pages, 2022.

[3] M. Moshagen and M. T. Thielsch, "Facets of visual aesthetics," *International Journal of Human-Computer Studies*, vol. 68, no. 10, pp. 689–709, 2010.

[4] N. Crilly, J. Moultrie, and P. J. Clarkson, "Seeing things: consumer response to the visual domain in product design," *Design Studies*, vol. 25, no. 6, pp. 547–577, 2004.

[5] N. Crilly, J. Moultrie, and P. J. Clarkson, "Shaping things: intended consumer response and the other determinants of product form," *Design Studies*, vol. 30, no. 3, pp. 224–254, 2009.

[6] P. H. Bloch, "Seeking the ideal form: product design and consumer response," *Journal of Marketing*, vol. 59, no. 3, p. 16, 1995.

[7] M. Berkowitz, "Product shape as a design innovation strategy," *Journal of Product Innovation Management*, vol. 4, no. 4, pp. 274–283, 1987.

[8] P. Hekkert, "Design aesthetics: principles of pleasure in design," *Psychological Science*, vol. 48, pp. 157–172, 2006.

[9] M. Berghman and P. Hekkert, "Towards a unified model of aesthetic pleasure in design," *New Ideas in Psychology*, vol. 47, pp. 136–144, 2017.

[10] M. Nagamachi, "Kansei Engineering: a new ergonomic consumer-oriented technology for product development," *International Journal of Industrial Ergonomics*, vol. 15, no. 1, pp. 3–11, 1995.

[11] E. Akgül, M. Özmen, C. Sinanoğlu, and E. Kizilkaya, "Rough Kansei mining model for market-oriented product design," *Mathematical Problems in Engineering*, vol. 2020, Article ID 6267031, 11 pages, 2020.

[12] C.-C. Yang, "A classification-based Kansei engineering system for modeling consumers' affective responses and analyzing product form features," *Expert Systems with Applications*, vol. 38, no. 9, pp. 11382–11393, 2011.

[13] M. Wagner, A. Curteza, Y. Hong, Y. Chen, S. Thomassey, and X. Zeng, "A design analysis for eco-fashion style using sensory evaluation tools: consumer perceptions of product appearance," *Journal of Retailing and Consumer Services*, vol. 51, pp. 253–262, 2019.

[14] S.-W. Hsiao, F.-Y. Chiu, and C. S. Chen, "Applying aesthetics measurement to product design," *International Journal of Industrial Ergonomics*, vol. 38, no. 11-12, pp. 910–920, 2008.

[15] M. Yamamoto and D. R. Lambert, "The impact of product aesthetics on the evaluation of industrial products," *Journal of Product Innovation Management*, vol. 11, no. 4, pp. 309–324, 1994.

[16] U. Bhandari, K. Chang, and T. Neben, "Understanding the impact of perceived visual aesthetics on user evaluations: an emotional perspective," *Information & Management*, vol. 56, no. 1, pp. 85–93, 2019.

[17] J. Hoegg, J. W. Alba, and D. W. Dahl, "The good, the bad, and the ugly: influence of aesthetics on product feature judgments," *Journal of Consumer Psychology*, vol. 20, no. 4, pp. 419–430, 2010.

[18] M. Hassenzahl, "The effect of perceived hedonic quality on product appealingness," *International Journal of Human-Computer Interaction*, vol. 13, no. 4, pp. 481–499, 2001.

[19] H. N. J. Schifferstein and P. Hekkert, *Product Experience. Product Experience*, Elsevier, Amsterdam, Netherlands, 2008.

[20] A. H. Goldman, *Aesthetic Value*, Westview Press, Boulder, CO, USA, 1995.

[21] Y. Reich, "A model of aesthetic judgment in design," *Artificial Intelligence in Engineering*, vol. 8, no. 2, pp. 141–153, 1993.

[22] J. Blijlevens, C. Thurgood, P. Hekkert, L.-L. Chen, H. Leder, and T. W. A. Whitfield, "The Aesthetic Pleasure in Design Scale: the development of a scale to measure aesthetic pleasure for designed artifacts," *Psychology of Aesthetics, Creativity, and the Arts*, vol. 11, no. 1, pp. 86–98, 2017.

[23] J. He, F. Li, Z. Li, and H. Liu, “The effect of mobile marketing design on consumer mobile shopping,” *Complexity*, vol. 2021, p. 10, 2021.

[24] S. H. Han and S. W. Hong, “A systematic approach for coupling user satisfaction with product design,” *Ergonomics*, vol. 46, no. 13-14, pp. 1441–1461, 2003.

[25] O. Demirbilek and B. Sener, “Product design, semantics and emotional response,” *Ergonomics*, vol. 46, no. 13-14, pp. 1346–1360, 2003.

[26] P. E. Green and V. R. Rao, “Conjoint measurement for quantifying judgmental data,” *Journal of Marketing Research*, vol. 8, no. 3, p. 355, 1971.

[27] R. D. Luce and J. W. Tukey, “Simultaneous conjoint measurement: a new type of fundamental measurement,” *Journal of Mathematical Psychology*, vol. 1, no. 1, pp. 1–27, 1964.

[28] H. Y. Chen and Y. M. Chang, “Extraction of product form features critical to determining consumers’ perceptions of product image using a numerical definition-based systematic approach,” *International Journal of Industrial Ergonomics*, vol. 39, no. 1, pp. 133–145, 2009.

[29] M. Wedel and R. Pieters, “Eye tracking for visual marketing,” *Foundations and Trends® in Microeconomics*, vol. 1, no. 4, pp. 231–320, 2006.

[30] R. Veryzer, Jr.Veryzer Jr and J. W. Hutchinson, “The influence of unity and prototypicality on aesthetic responses to new product designs,” *Journal of Consumer Research*, vol. 24, no. 4, pp. 374–385, 1998.

[31] A. Todorov, “Evaluating faces on social dimensions,” *Social Neuroscience: Toward Understanding the Underpinnings of the Social Mind*, pp. 54–76, Oxford University Press, Oxford, UK, 2011.

[32] R. Dotsch and A. Todorov, “Reverse correlating social face perception,” *Social Psychological and Personality Science*, vol. 3, no. 5, pp. 562–571, 2012.

[33] L. Brinkman, A. Todorov, and R. Dotsch, “Visualising mental representations: a primer on noise-based reverse correlation in social psychology,” *European Review of Social Psychology*, vol. 28, no. 1, pp. 333–361, 2017.

[34] H. Dai and C. Micheyl, “Psychophysical reverse correlation with multiple response alternatives,” *Journal of Experimental Psychology: Human Perception and Performance*, vol. 36, no. 4, pp. 976–993, 2010.

[35] J. C. Jackson, N. Hester, and K. Gray, “The faces of god in America: revealing religious diversity across people and politics,” *PLoS One*, vol. 13, no. 6, Article ID e0198745, 2018.

[36] R. Dotsch and D. H. J. Wigboldus, “Virtual prejudice,” *Journal of Experimental Social Psychology*, vol. 44, no. 4, pp. 1194–1198, 2008.

[37] E. Hehman, J. K. Flake, and J. B. Freeman, “Static and dynamic facial cues differentially affect the consistency of social evaluations,” *Personality and Social Psychology Bulletin*, vol. 41, no. 8, pp. 1123–1134, 2015.

[38] R. Imhoff, J. Woelki, S. Hanke, and R. Dotsch, “Warmth and competence in your face! Visual encoding of stereotype content,” *Frontiers in Psychology*, vol. 4, p. 386, 2013.

[39] J. R. Kunst, J. F. Dovidio, and R. Dotsch, “White look-alikes: mainstream culture adoption makes immigrants “look” phenotypically white,” *Personality and Social Psychology Bulletin*, vol. 44, no. 2, pp. 265–282, 2018.

[40] M. C. Mangini and I. Biederman, “Making the ineffable explicit: estimating the information employed for face classifications,” *Cognitive Science*, vol. 28, no. 2, pp. 209–226, 2004.

[41] V. Bruce and A. Young, *Face Perception*, Psychology Press, New York, NY, 2012.

[42] R. Poveda-Bautista, J. A. Diego-Mas, and J. Alcaide-Marzal, “Analysis of the visual perception of the competences of project managers,” *Sustainability*, vol. 13, no. 9, p. 4984, 2021.

[43] J. A. Diego-Mas, F. Fuentes-Hurtado, V. Naranjo, and M. Alcañiza, “Effect Size of the Appearance of Each Facial Feature on How We Perceive and Interpret Human Faces,” in *Proceedings of the 24th International Congress on Project Management and Engineering*, pp. 84–91, Alcoi, Spain, July 2020.

[44] J.-A. Diego-Mas, F. Fuentes-Hurtado, V. Naranjo, and M. Alcañiz, “The influence of each facial feature on how we perceive and interpret human faces,” *I-Perception*, vol. 11, no. 5, Article ID 204166952096112, 2020.

[45] F. Fuentes-Hurtado, J. A. Diego-Mas, V. Naranjo, and M. Alcañiz, “Automatic classification of human facial features based on their appearance,” *PLoS One*, S. Mirjalili, Ed., vol. 14, no. 1, Article ID e0211314, 2019.

[46] F. Fuentes-Hurtado, J. A. Diego-Mas, V. Naranjo, and M. Alcañiz, “Evolutionary computation for modelling social traits in realistic looking synthetic faces,” *Complexity*, vol. 2018, pp. 1–16, 2018.

[47] N. van Rijsbergen, K. Jaworska, G. A. Rousselet, and P. G. Schyns, “With age comes representational wisdom in social signals,” *Current Biology*, vol. 24, no. 23, pp. 2792–2796, 2014.

[48] N. Kanwisher, J. McDermott, and M. M. Chun, “The fusiform face area: a module in human e cortex specialized for face perception,” *Journal of Neuroscience*, vol. 17, no. 11, pp. 4302–4311, Article ID 9151747, 1997.

[49] D. W. Piepers and R. A. Robbins, “A review and clarification of the terms “holistic,” “configural,” and “relational” in the face perception literature,” *Frontiers in Psychology*, vol. 3, p. 559, 2012.

[50] J. W. Tanaka and M. J. Farah, “Parts and wholes in face recognition,” *The Quarterly Journal of Experimental Psychology Section A*, vol. 46, no. 2, pp. 225–245, 1993.

[51] A. W. Young, D. Hellawell, and D. C. Hay, “Configurational information in face perception,” *Perception*, vol. 16, no. 6, pp. 747–759, 1987.

[52] J. L. Voss, K. D. Federmeier, and K. A. Paller, “The potato chip really does look like elvis! Neural hallmarks of conceptual processing associated with finding novel shapes subjectively meaningful,” *Cerebral Cortex*, vol. 22, no. 10, pp. 2354–2364, 2012.

[53] S. Bentin, N. Sagiv, A. Mecklinger, A. Friederici, and Y. D. von Cramon, “Priming visual face-processing mechanisms: electrophysiological evidence,” *Psychological Science*, vol. 13, no. 2, pp. 190–193, 2002.

[54] S. Bentin, T. Allison, A. Puce, E. Perez, and G. McCarthy, “Electrophysiological studies of face perception in humans,” *Journal of Cognitive Neuroscience*, vol. 8, no. 6, pp. 551–565, 1996.

[55] S. Kühn, T. R. Brick, B. C. N. Müller, and J. Gallinat, “Is this car looking at you? How anthropomorphism predicts fusiform face area activation when seeing cars,” *PLoS One*, vol. 9, no. 12, Article ID e113885, 2014.

[56] P. Aggarwal and A. L. McGill, “Is that car smiling at me? Schema congruity as a basis for evaluating anthropomorphized products,” *Journal of Consumer Research*, vol. 34, no. 4, pp. 468–479, 2007.

[57] R. E. Jack, R. Caldara, and P. G. Schyns, “Internal representations reveal cultural diversity in expectations of facial expressions of emotion,” *Journal of Experimental Psychology: General*, vol. 141, no. 1, pp. 19–25, 2012.

[58] F. Gosselin, B. A. Bacon, and P. Mamassian, “Internal surface representations approximated by reverse correlation,” *Vision Research*, vol. 44, no. 21, pp. 2515–2520, 2004.

[59] R. Dotsch, “Rcicr: Reverse-Correlation Image-Classification Toolbox,” 2016, https://cran.r-project.org/web/packages/rcicr/index.html.

[60] B. Piqueras-fiszman, G. Ares, J. Alcaide-marzal, and J. A. Diego-Más, “Comparing older and younger users' perceptions of mobile phones and watches using c questions and preference mapping on the design characteristics,” *Journal of Sensory Studies*, vol. 26, no. 1, pp. 1–12, 2011.

[61] A. Todorov, R. Dotsch, D. H. J. Wigboldus, and C. P. Said, “Data-driven methods for modeling social perception,” *Social and Personality Psychology Compass*, vol. 5, no. 10, pp. 775–791, 2011.

[62] L. Brinkman, S. Goffin, R. van de Schoot, N. E. M. van Haren, R. Dotsch, and H. Aarts, “Quantifying the informational value of classification images,” *Behavior Research Methods*, vol. 51, no. 5, pp. 2059–2073, 2019.

[63] R. Imhoff and R. Dotsch, “Do we look like me or like us? Visual projection as self- or ingroup-projection,” *Social Cognition*, vol. 31, no. 6, pp. 806–816, 2013.

Hindawi
Complexity
Volume 2022, Article ID 3243450, 8 pages
https://doi.org/10.1155/2022/3243450

Research Article

Application of RQMC for CDO Pricing with Stochastic Correlations under Nonhomogeneous Assumptions

Shuanghong Qu,[1] **Lingxian Meng**,[1] **and Hua Li**[2,3]

[1] *College of Mathematics and Information Science, Zhengzhou University of Light Industry, Zhengzhou 450002, China*
[2] *School of Mathematics and Statistics, Zhengzhou University, Zhengzhou 450001, China*
[3] *Henan Key Lab of Financial Engineering, Zhengzhou University, Zhengzhou 450001, China*

Correspondence should be addressed to Hua Li; huali08@zzu.edu.cn

Received 22 February 2022; Revised 31 March 2022; Accepted 18 May 2022; Published 31 July 2022

Academic Editor: Ning (Chris) Chen

In consideration of that the correlation between any two assets of the asset pool is always stochastic in the actual market and that collateralized debt obligation (CDO) pricing models under nonhomogeneous assumptions have no semianalytic solutions, we designed a numerical algorithm based on randomized quasi-Monte Carlo (RQMC) simulation method for CDO pricing with stochastic correlations under nonhomogeneous assumptions and took Gaussian factor copula model as an example to conduct experiments. The simulation results of RQMC and Monte Carlo (MC) method were compared from the perspective of variance changes. The results showed that this numerical algorithm was feasible, efficient, and stable for CDO pricing with stochastic correlation under nonhomogeneous assumptions. This numerical algorithm is expected to be extended to other factor Copula models for CDO pricing with stochastic correlations under nonhomogeneous assumptions.

1. Introduction

Collateralized debt obligation (CDO) is one of the most typical securitized assets in credit derivative markets, and its pricing has always been the focus of scholars. In the pricing process of CDO, the reduced model is widely used for establishing default distribution of a single reference entity, factor Copula methods are the mainstream of joint default distribution of asset portfolio [1, 2], and the spread of each tranche of CDO can be calculated according to the principle of arbitrage-free pricing [3].

The Gaussian factor Copula model is usually considered to be the standard model for CDO pricing, but its correlation coefficient is a deterministic parameter. In fact, the stochastic correlation copula is closer to the market [3]. Therefore, some scholars extended the constant correlation coefficient to a stochastic one. Burtschell et al. [4] provided a thorough analysis of the three-state stochastic correlation model with homogeneity and obtained the semianalytical pricing formula. Yang et al. [5] proposed a semianalytical method for the credit spreads of each CDO tranche under the conditions of homogeneity and stochastic correlations based on single-factor Copula model with mixed distribution.

As we can see, the above literature is all based on the assumption of homogeneity. However, it is difficult to meet the requirements of homogeneity in actual markets and the arbitrage-free pricing models under nonhomogeneous assumptions have no semianalytical solutions [6]. Therefore, it might be a good idea to resort to numerical methods.

Monte Carlo (MC) is one of the most common numerical methods [7, 8]. However, this method has a certain dimension disaster problem. Quasi-Monte Carlo (QMC) [9, 10] is an extension of MC, and it is usually superior to MC in dealing with high-dimensional problems. Furthermore, by introducing a randomized component into the QMC method, the randomized quasi-Monte Carlo (RQMC) method can effectively improve the cycle problem [11], which usually has higher convergence order than MC and QMC. Some scholars applied RQMC to option pricing [12–14]. Johansson et al. [12] studied the pricing of American options using RQMC and found that RQMC could reduce both the variance and the bias of the option. Amal et al. [13] applied array-RQMC for option pricing under a stochastic volatility process, and the empirical results showed that it could bring very significant variance reductions compared with MC. He [14] found that RQMC had a better rate of convergence in financial option pricing.

Qu et al. [15] introduced RQMC into the CDO pricing based on a single-factor Copula framework and nonhomogeneous hypothesis and achieved good results. However, only the constant correlation coefficient was considered in the model. To our knowledge, there have been no further reports of RQMC being used to solve the CDO pricing issues. In view of this, we intend to design a numerical algorithm for the CDO pricing with stochastic correlations based on RQMC and Gaussian factor Copula model under the conditions of nonhomogeneous assumptions and conduct empirical research. We try to provide some ideas for the pricing problem with stochastic correlations under the nonhomogeneous assumptions in the credit derivative markets.

The rest of this paper is organized as follows: Some preliminary knowledge is introduced in Section 2. In the following section, the concrete algorithm process is given based on RQMC. The empirical study is carried out in Section 4. Finally, the conclusion and the discussion are presented in Section 5.

2. Methodology

2.1. Arbitrage-Free Pricing Model. First, we give some symbols used in this paper and their meanings are shown in Table 1.

According to the principle of arbitrage-free pricing, for the m-th tranche, the discounted expectation of premium leg (PL) and default leg (DL) should be equal, i.e.,

$$E(\mathrm{PL}[a_{m-1}, a_m]) = E(\mathrm{DL}[a_{m-1}, a_m]), \quad m = 1, 2, \ldots, M. \tag{1}$$

In the continuous case, they can be expressed as follows:

$$E(\mathrm{PL}[a_{m-1}, a_m]) = E\left[\int_0^T s_m E_m(t) e^{-r_f t} \mathrm{d}t\right] \approx s_m (A_m + B_m), \tag{2}$$

$$E(\mathrm{DL}[a_{m-1}, a_m]) = E\left[\int_0^T e^{-r_f t} \mathrm{d}L_m(t)\right] \approx C_m. \tag{3}$$

From equations (1)–(3), we have

$$s_m = \frac{C_m}{A_m + B_m} \quad m = 1, 2, \ldots, M. \tag{4}$$

2.2. Gaussian Factor Copula Model with Stochastic Correlations. In Gaussian factor Copula model with stochastic correlations, the yield rate $X_i\,(i = 1, 2, \ldots, n)$ of the i-th asset is determined by a common factor F and a special factor $Z_i\,(i = 1, 2, \ldots, n)$, namely,

$$X_i = \sqrt{\tilde{\rho}_i} F + \sqrt{1 - \tilde{\rho}_i} Z_i, \quad i = 1, 2, \ldots, n, \tag{5}$$

where F and $Z_i\,(i = 1, 2, \ldots, n)$ are independent of each other and they are all subject to $N(0, 1)$; $\tilde{\rho}_i\,(i = 1, 2, \ldots, n)$ are stochastic correlation coefficients between $X_i\,(i = 1, 2, \ldots, n)$ and F, and it is independent of F and $Z_i\,(i = 1, 2, \ldots, n)$; $X_i\,(i = 1, 2, \ldots, n)$ is also independent of each other when F and $\tilde{\rho}_i\,(i = 1, 2, \ldots, n)$ are conditions. The distribution functions of F, Z_i, and X_i are denoted as G_F, G_{Z_i}, and G_{X_i}, respectively, where $i = 1, 2, \ldots, n$.

Now, we consider the case that the random variable $\tilde{\rho}_i$ of equation (5) is in two states.

State 1. When $\tilde{\rho}_i = \rho_i\,(i = 1, 2, \ldots, n)$, equation (5) can be written as

$$X_i = \sqrt{\rho_i} F + \sqrt{1 - \rho_i} Z_i \quad i = 1, 2, \ldots, n. \tag{6}$$

The probability of this state is p.

State 2. When $\tilde{\rho}_i = \eta_i\,(i = 1, 2, \ldots, n)$, we have

$$X_i = \sqrt{\eta_i} F + \sqrt{1 - \eta_i} Z_i \quad i = 1, 2, \ldots, n. \tag{7}$$

In this case, the probability is $1 - p$.

We point out that in this paper, we use corresponding superscript symbols (1) and (2) to indicate States 1 and 2, respectively.

For the m-th tranche, according to equation (4), we have

$$s_m^{(1)} = \frac{C_m^{(1)}}{A_m^{(1)} + B_m^{(1)}}, \quad m = 1, 2, \ldots, M, \tag{8}$$

$$s_m^{(2)} = \frac{C_m^{(2)}}{A_m^{(2)} + B_m^{(2)}}, \quad m = 1, 2, \ldots, M. \tag{9}$$

Now, let us take State 1 as an example to illustrate.

In State 1, according to the reduced model, the accumulative probability of the i-th asset defaulting before $t_i^{(1)}$ can be written as

$$Q_{\mathcal{T}_i^{(1)}}\left(t_i^{(1)}\right) = 1 - e^{-\lambda_i^{(1)} t_i^{(1)}}, \tag{10}$$

where $\lambda_i^{(1)}$ is the default intensity of the i-th asset and $\mathcal{T}_i^{(1)}$ is default time. For the i-th asset, we know that the default correlation of yield rate $X_i^{(1)}$ can be reflected by the correlation of default time $\mathcal{T}_i^{(1)}$, so we can assume that the relationship between $\mathcal{T}_i^{(1)}$ and $X_i^{(1)}$ can be described as

$$P\left\{X_i^{(1)} \le x_i^{(1)}\right\} = P\left\{\mathcal{T}_i^{(1)} \le t_i^{(1)}\right\}, \tag{11}$$

namely,

$$G_{X_i^{(1)}}\left(x_i^{(1)}\right) = Q_{\mathcal{T}_i^{(1)}}\left(t_i^{(1)}\right). \tag{12}$$

Then, according to equations (10)–(12), $t_i^{(1)}$ can be obtained:

$$t_i^{(1)} = Q_{\mathcal{T}_i^{(1)}}^{-1}\left(G_{X_i^{(1)}}\left(x_i^{(1)}\right)\right) = -\frac{\ln\left(1 - G_{X_i^{(1)}}\left(x_i^{(1)}\right)\right)}{\lambda_i^{(1)}}. \tag{13}$$

Table 1: Symbols and their meanings.

Symbol	Meaning	Note
n	Number of reference entities in the asset pool of CDO	
N_i	Nominal value of the i-th reference entity	$i = 1, 2, \ldots, n$
N	Total nominal value	$N = \sum_{i=1}^{n} N_i$
R_i	Recovery rate of the i-th reference entity	$i = 1, 2, \ldots, n$
l_i	Loss of the i-th reference entity	$l_i = N_i(1 - R_i)$, $i = 1, 2, \ldots, n$
$L(t)$	Accumulative default loss at time t	$L(t) = \sum_{i=1}^{n} l_i 1_{\{\mathcal{T}_i \le t\}}, 1_{\{\mathcal{T}_i \le t\}} = \begin{cases} 1, & \text{if } \mathcal{T}_i \le t \\ 0, & \text{if } \mathcal{T}_i > t \end{cases}$
r_f	Risk-free interest rates	
T	Term of CDO	Unit: year
τ_j	Payment of time nodes	$j = 1, 2, \ldots, J, \tau_J = T$
$\Delta\tau_j$	Payment interval	$\Delta\tau_j = \tau_j - \tau_{j-1}, j = 1, 2, \ldots, J, \tau_0 = 0$
M	Total number of tranches	
$[a_{m-1,} a_m]$	The m-th tranche	$m = 1, 2, \ldots, M$
$L_m(t)$	Loss suffered by the m-th tranche at time t	$L_m(t) = \max\{L(t) - Na_{m-1}, 0\} - \max\{L(t) - Na_m, 0\}, m = 1, 2, \ldots, M$
$E_m(t)$	Residual value of the m-th tranche at time t	$E_m(t) = Na_m - Na_{m-1} - L_m(t), m = 1, 2, \ldots, M$
s_m	Spread of the m-th tranche	
$s_m\ A_m$	Discounted value of normal payment for promotion of the m-th tranche	
$s_m\ B_m$	Accrual payment of the m-th tranche when default occurs	$m = 1, 2, \ldots, M$
C_m	Discounted value of compensation of the m-th tranche	

By substituting $t_i^{(1)}$ into equations (2) and (3), $s_m^{(1)}$ $(m = 1, \ldots, M)$ can be obtained by equation (8).

Similarly, the corresponding default time $t_i^{(2)}$ in State 2 can be obtained as follows:

$$t_i^{(2)} = Q_{\mathcal{T}_i^{(2)}}^{-1}\left(G_{X_i^{(2)}}\left(x_i^{(2)}\right)\right) = -\frac{\ln\left(1 - G_{X_i^{(2)}}\left(x_i^{(2)}\right)\right)}{\lambda_i^{(2)}}, \tag{14}$$

where $\lambda_i^{(2)}$ is default intensity of the i-th asset in State 2. Then, $s_m^{(2)}$ $(m = 1, \ldots, M)$ can be obtained.

Finally, we have

$$s_m = p s_m^{(1)} + (1 - p) s_m^{(2)}, \quad m = 1, \ldots, M. \tag{15}$$

2.3. Random Sobol Sequences. Figure 1 shows the scatter diagrams of pseudo-random sequences used in MC, Sobol sequences used in QMC, and randomized Sobol (Sobol scramble) sequences used in RQMC in high-dimensional cases (125-th dimension and 126-th dimension), respectively, where the number of points are all 1100.

It can be seen from Figure 1 that randomized Sobol sequences not only maintain good uniformity but also improve circulation problems of Sobol sequences in high dimension. In this paper, RQMC method based on randomized Sobol sequences is adopted.

In this paper, we call command equation (16) in MATLAB to generate $(n+1)$-dimensional Sobol sequences and $(n+1)$-dimensional randomized Sobol sequences.

$$P = \text{sobolset}(n+1); P = \text{scramble} \cdot (P, \text{'Matousek Affine Owen'}). \tag{16}$$

3. Algorithm

In this section, based on the Gaussian factor Copula model, we design the RQMC simulation algorithm for CDO pricing with stochastic correlations of the two states under nonhomogeneous assumptions.

First, we draw the algorithm flow chart (concise format), as shown in Figure 2. The meanings of ρ_i, η_i, p, and ST are shown in Step 1 of the algorithm.

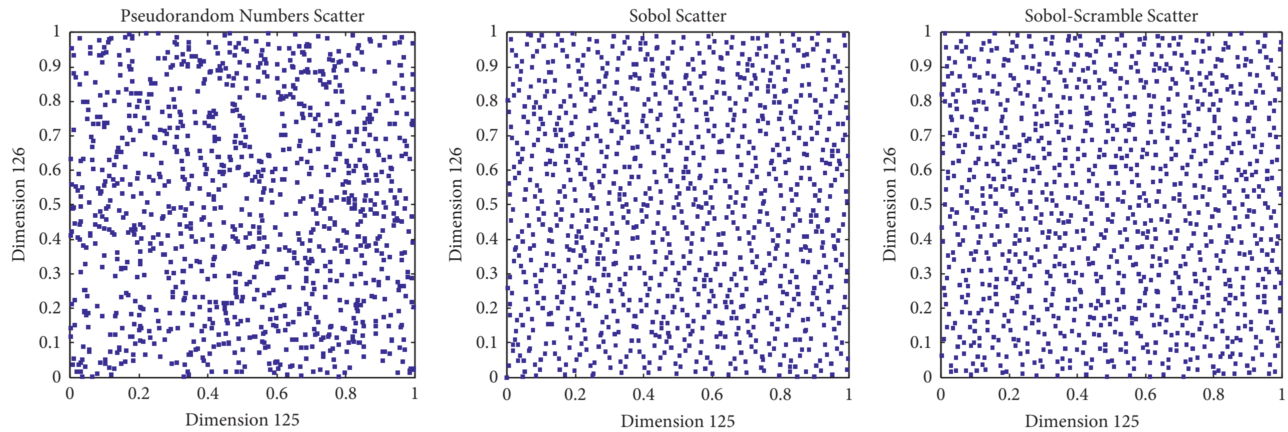
Next, we give the concrete steps of the algorithm.

Step 1. Determine and input the relevant data.

Assume that there are only two values ρ_i and η_i for stochastic correlation coefficients $\tilde{\rho}_i$ and corresponding probabilities are p and $1 - p$, respectively, where $i = 1, \ldots, n$. In addition, we preset the total number of simulations, denoted as ST.

Step 2. Generate randomized Sobol sequences.

$(n+1)$-dimensional randomized sequences $(\varepsilon_0, \varepsilon_1, \ldots, \varepsilon_n)$ are generated by command equation (16); then, we can get corresponding sequences $(G_F^{-1}(\varepsilon_0), G_{Z_1}^{-1}(\varepsilon_1), \ldots, G_{Z_n}^{-1}(\varepsilon_n))$, which is a set of values $(F, Z_1, \ldots, Z_n)$, denoted as $(y, z_1, \ldots, z_n)$.



(a) (b) (c)

FIGURE 1: Scatter plots of different sequences.

Step 3. Simulate a path of yields in the two states, respectively.

Substitute $y, z_i\,(i = 1, \ldots, n)$ obtained in Step 2 and $\rho_i\,(i = 1, \ldots, n)$ determined in Step 1 into equation (6) to get the corresponding values $x_i^{(1)}\,(i = 1, \ldots, n)$ of yield rates $X_i^{(1)}\,(i = 1, \ldots, n)$ in State 1, and substitute $y, z_i\,(i = 1, \ldots, n)$ and $\eta_i\,(i = 1, \ldots, n)$ into equation (7) to get the corresponding values $x_i^{(2)}\,(i = 1, \ldots, n)$ of yield rates $X_i^{(2)}\,(i = 1, \ldots, n)$ in State 2.

Step 4. Generate default times in the two states, respectively.

Substitute $x_i^{(1)}$ and $x_i^{(2)}\,(i = 1, \ldots, n)$ obtained in Step 3 into equations (13) and (14); then, we can obtain $t_i^{(1)}, t_i^{(2)}\,(i = 1, \ldots, n)$.

Step 5. Find out the actual default time in the two states.

Find out the actual default time for the two states: $\left\{\tilde{t}_k^{(1)} | \tilde{t}_k^{(1)} \in \left\{t_i^{(1)} | t_i^{(1)} \le T,\ i = 1, \ldots, n\right\},\ k = 1, 2, \ldots, K_1\right\}$ and $\left\{\tilde{t}_k^{(2)} | \tilde{t}_k^{(2)} \in \left\{t_i^{(2)} | t_i^{(2)} \le T,\ i = 1, \ldots, n\right\},\ k = 1, \ldots, K_2\right\}$, where $K_1\,(K_1 \le n)$ and $K_2\,(K_2 \le n)$ are the total number of real default assets in the two states, respectively. Here, we agree that $\tilde{t}_k^{(1)}\,(k = 1, 2, \ldots, K_1)$ and $\tilde{t}_k^{(2)}\,(k = 1, 2, \ldots, K_2)$ have been arranged in an order from the smallest to the largest, i.e.,

$$\begin{aligned} &\tilde{t}_k^{(1)} \le \tilde{t}_{k+1}^{(1)}\,(k = 1, 2, \ldots K_1 - 1), \\ &\tilde{t}_k^{(2)} \le \tilde{t}_{k+1}^{(2)}\,(k = 1, 2, \ldots K_2 - 1). \end{aligned} \tag{17}$$

We introduce default matrices $L^{(1)}$ and $L^{(2)}$:

$$\begin{aligned} L^{(1)} &= \begin{pmatrix} \tilde{t}_1^{(1)} & \tilde{t}_2^{(1)} & \tilde{t}_3^{(1)} & \ldots & \tilde{t}_{K_1}^{(1)} \\ h_1^{(1)} & h_2^{(1)} & h_3^{(1)} & \ldots & h_{K_1}^{(1)} \\ H_1^{(1)} & H_2^{(1)} & H_3^{(1)} & \ldots & H_{K_1}^{(1)} \end{pmatrix}, \\ L^{(2)} &= \begin{pmatrix} \tilde{t}_1^{(2)} & \tilde{t}_2^{(2)} & \tilde{t}_3^{(2)} & \ldots & \tilde{t}_{K_2}^{(2)} \\ h_1^{(2)} & h_2^{(2)} & h_3^{(2)} & \ldots & h_{K_2}^{(2)} \\ H_1^{(2)} & H_2^{(2)} & H_3^{(2)} & \ldots & H_{K_2}^{(2)} \end{pmatrix}. \end{aligned} \tag{18}$$

where $h_k^{(1)}\,(k = 1, 2, \ldots K_1)$ and $h_k^{(2)}\,(k = 1, 2, \ldots K_2)$ are the corresponding nominal values of the k-th real default in the two states, respectively, and $H_k^{(1)}\,(k = 1, 2, \ldots K_1)$ and $H_k^{(2)}\,(k = 1, 2, \ldots K_2)$ are the corresponding cumulative nominal values of the k-th real default by time $\tilde{t}_k^{(1)}$ and $\tilde{t}_k^{(2)}$, respectively.

Step 6. Allocate default losses for the two states.

Let $b_m^{(1)}$ and $b_m^{(2)}$ be the corresponding positions of the maximum loss that the m-th tranche can bear in $L^{(1)}$ and $L^{(2)}$, respectively, which means that $H_{b_m^{(1)}}^{(1)}(1 - R) = a_m, H_{b_m^{(2)}}^{(2)}(1 - R) = a_m$, where a_m is a separation point (maximum loss should be taken by the m-th tranche); then, the default information allocated to the m-th tranche in the two states can be represented by the following default matrices:

$$\begin{aligned} L_m^{(1)} &= \begin{pmatrix} \tilde{t}_{b_{m-1}+1}^{(1)} & \tilde{t}_{b_{m-1}+2}^{(1)} & \ldots & \tilde{t}_{b_m}^{(1)} \\ h_{b_{m-1}+1}^{(1)} & h_{b_{m-1}+2}^{(1)} & \ldots & h_{b_m}^{(1)} \\ H_{b_{m-1}+1}^{(1)} & H_{b_{m-1}+2}^{(1)} & \ldots & H_{b_m}^{(1)} \end{pmatrix}, \\ L_m^{(2)} &= \begin{pmatrix} \tilde{t}_{b_{m-1}+1}^{(2)} & \tilde{t}_{b_{m-1}+2}^{(2)} & \ldots & \tilde{t}_{b_m}^{(2)} \\ h_{b_{m-1}+1}^{(2)} & h_{b_{m-1}+2}^{(2)} & \ldots & h_{b_m}^{(2)} \\ H_{b_{m-1}+1}^{(2)} & H_{b_{m-1}+2}^{(2)} & \ldots & H_{b_m}^{(2)} \end{pmatrix}. \end{aligned} \tag{19}$$

Step 7. Calculate $A_m^{(1)}, B_m^{(1)}, C_m^{(1)}$ and $A_m^{(2)}, B_m^{(2)}, C_m^{(2)}$.

For the m-th tranche $[a_{m-1}, a_m]\,(m = 1, \ldots, M)$, the initial nominal values are $E_0^{(m)^{(1)}} = E_0^{(m)^{(1)}} = N\mathrm{a}_m - N\mathrm{a}_{m-1}$ and we can calculate the residual values of States 1 and 2 at τ_j:

$$\begin{aligned} E_j^{(m)^{(1)}} &= E_{j-1}^{(m)^{(1)}} - \sum_{k \in \Omega_1} (1 - R) h_k^{(1)}, \quad j = 1, \ldots, J_1 \\ E_j^{(m)^{(2)}} &= E_{j-1}^{(m)^{(2)}} - \sum_{k \in \Omega_2} (1 - R) h_k^{(2)}, \quad j = 1, \ldots, J_2. \end{aligned} \tag{20}$$

Here, $\Omega_1 = \left\{k \mid \tau_{j-1} \le \tilde{t}_k^{(1)} \le \tau_j, b_{m-1}^{(1)} + 1 \le k \le b_m^{(1)}\right\}$ and $\Omega_2 = \left\{k \mid \tau_{j-1} \le \tilde{t}_k^{(2)} \le \tau_j, b_{m-1}^{(2)} + 1 \le k \le b_m^{(2)}\right\}$. Then, we have

$$\begin{aligned}
A_m^{(1)} &= \sum_{j=1}^{J_1} \Delta\tau \times E_j^{(m)^{(1)}} \times e^{-r_f \tau_j}, \\
B_m^{(1)} &= \sum_{k=b_{m-1}^{(1)}+1}^{b_m^{(1)}} \left(\tilde{t}_k^{(1)} - t_*^{(1)}\right) \times h_k^{(1)} \times (1-R) \times e^{-r_f \tilde{t}_k^{(1)}}, \\
C_m^{(1)} &= \sum_{k=b_{m-1}^{(1)}+1}^{b_m^{(1)}} h_k^{(1)} \times (1-R) \times e^{-r_f \tilde{t}_k^{(1)}}, \\
A_m^{(2)} &= \sum_{j=1}^{J_2} \Delta\tau \times E_j^{(m)^{(2)}} \times e^{-r_f \tau_j}, \\
B_m^{(2)} &= \sum_{k=b_{m-1}^{(2)}+1}^{b_m^{(2)}} \left(\tilde{t}_k^{(2)} - t_*^{(2)}\right) \times h_k^{(2)} \times (1-R) \times e^{-r_f \tilde{t}_k^{(2)}}, \\
C_m^{(2)} &= \sum_{k=b_{m-1}^{(2)}+1}^{b_m^{(2)}} h_k^{(2)} \times (1-R) \times e^{-r_f \tilde{t}_k^{(2)}},
\end{aligned} \tag{21}$$

where $t_*^{(1)}$ and $t_*^{(2)}$ are the last coupon payment time periods nearest to $\tilde{t}_k^{(1)}$ and $\tilde{t}_k^{(2)}$ in the two states, respectively.

Note: at this point, the values of $A_m^{(1)}, B_m^{(1)}, C_m^{(1)}$ and $A_m^{(2)}, B_m^{(2)}, C_m^{(2)}$ of the m-th coupon on a path have been calculated, where $m = 1, \ldots, M$.

Repeat Steps 2–7 until the total number of simulations reaches ST.

Step 8. Calculate $s_m \, (m = 1, \ldots, M)$.

For $m = 1, 2, \ldots, M$, we calculate the average values of $A_m^{(1)}, B_m^{(1)}, C_m^{(1)}$ and $A_m^{(2)}, B_m^{(2)}, C_m^{(2)}$, respectively, and denote them as $\overline{A_m^{(1)}}, \overline{B_m^{(1)}}, \overline{C_m^{(1)}}$ and $\overline{A_m^{(2)}}, \overline{B_m^{(2)}}, \overline{C_m^{(2)}}$ in sequence. Then, we substitute $\overline{A_m^{(1)}}, \overline{B_m^{(1)}}, \overline{C_m^{(1)}}$ into equation (8) to obtain $s_m^{(1)}$ and substitute $\overline{A_m^{(2)}}, \overline{B_m^{(2)}}, \overline{C_m^{(2)}}$ into equation (9) to obtain $s_m^{(2)}$. Finally, we plug $s_m^{(1)} \, (m = 1, \ldots, M)$ and $s_m^{(2)} \, (m = 1, \ldots, M)$, and the value of p into equation (15) to get $s_m \, (m = 1, \ldots, M)$.

This is the end of the algorithm.

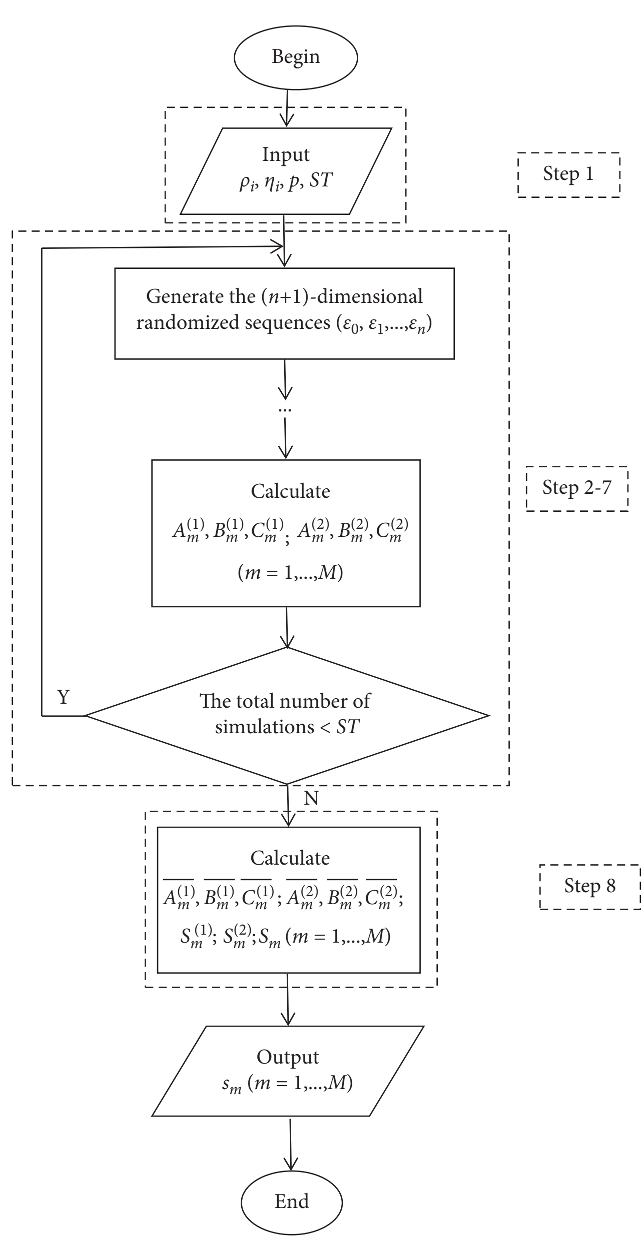


Figure 2: Algorithm flow chart (concise format).

4. Empirical Study

4.1. Parameter Values. In this paper, the values of each parameter are as follows (refer to [3]). Let $n = 125$, $N = 1$, the nominal value and return rate of each reference entity be all equal, respectively; that is, $N_i = 1/n$, $R_i = R = 0.4$, and payment intervals are all $\Delta\tau = 0.25$. Let $r_f = 0.035$ and duration $T = 5$ (year). CDO tranches are [0, 3%], [3%, 6%], [6%, 9%], [9%, 12%], [12%, 22%], and [22%, 100%]. We assume that the default intensity is equal, that is, $\lambda_i^{(1)} = \lambda_i^{(2)} = \lambda = 0.0083$, and the Copula correlation coefficients of the two states are all equal, respectively; let $\rho_i = \rho = 0.12$, $\eta_i = \eta = 0.21$, and the probability of state 1 be $p = 0.3$. (Note: in the practical application, corresponding values of ρ_i and η_i are just substituted into equations (6) and (7), respectively; the default intensities $\lambda_i^{(1)}$ and $\lambda_i^{(2)}$ are just substituted into equations (13) and (14), respectively; and other steps in Section 3 are all the same.)

4.2. Result Analysis. In order to investigate the stability of simulation results of the RQMC method and MC method, we calculate the variances of the two simulation methods under different simulation times and observe their changes for each CDO tranche, respectively. We set the variation range of simulation times from 5000 to 50000, with the step size of 5000. For each different simulation times, we all simulate 40 times and then calculate the corresponding variances of MC and RQMC of each CDO tranche. The variance changes of the simulation results of the two

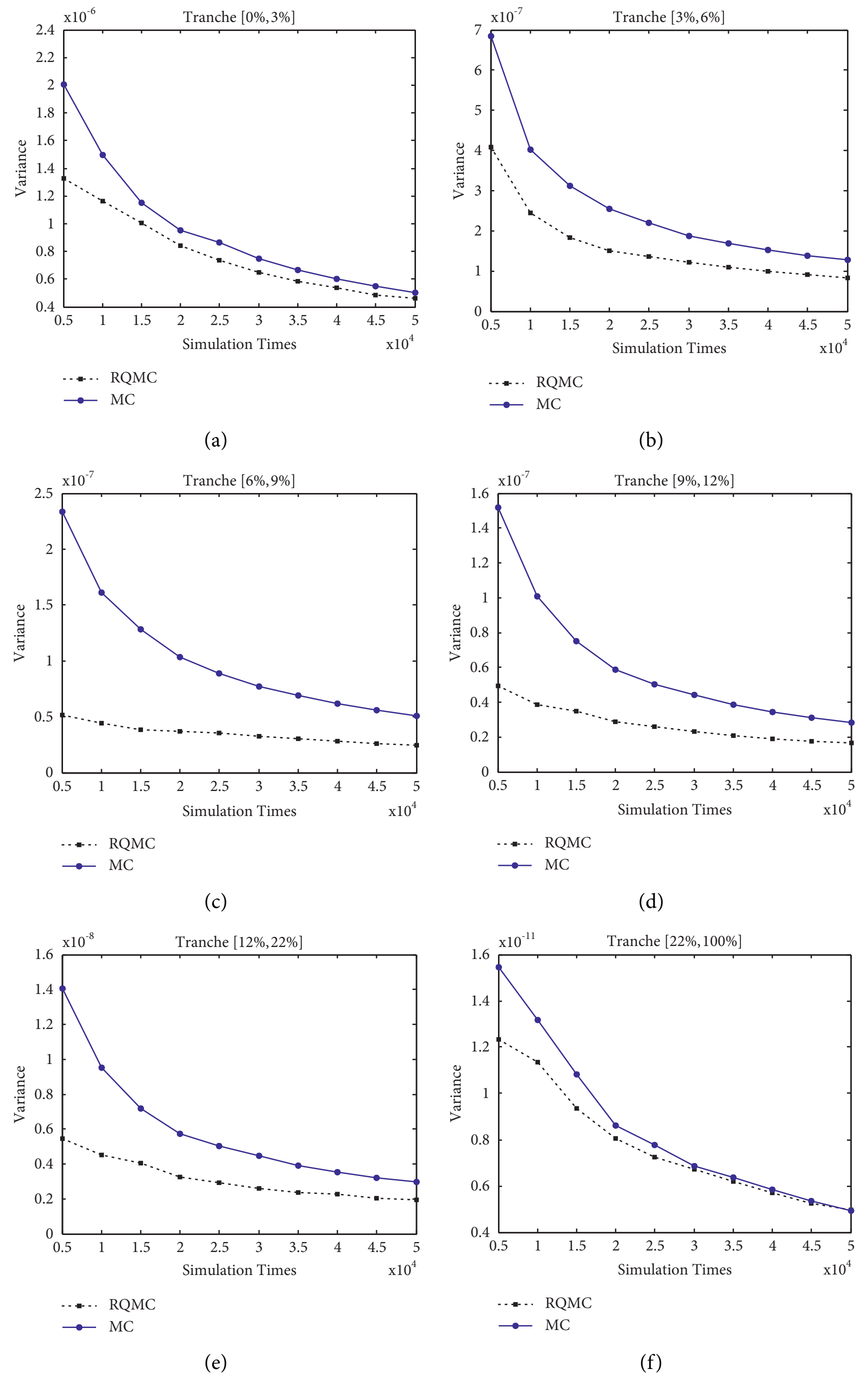


Figure 3: Variance changes of CDO pricing in each tranche with the increase in simulation times.

simulation methods for the pricing of each CDO tranche with the increase in simulation times are shown in Figure 3.

On the whole, we can see from Figure 3 that the variances of the two simulation methods in six different tranches are all decreased with the increase in simulation times, and in each subgraph, the gaps between the two curves all reduce gradually with the increase in simulation times. These show that the results of the two simulation methods are all gradually stable with the increase in simulation times. It can also be seen from Figure 3 that, compared with the MC method, the variance changes of each CDO tranche of the RQMC method are more gentle with the increase in simulation times. Especially, when the simulation time is relatively smaller, with the increase in simulation times, the variances of MC all decrease faster than those of RQMC in each CDO tranche. This indicates that the simulation results of the RQMC method are more stable than those of MC even when the simulation time is not too large. In other words, the RQMC method can obtain more stable results with fewer simulation times.

Table 2: Comparison of simulation times required of MC and RQMC at the same variance (taking 50000 times of simulation of MC as an example).

Tranches	Variance	Simulation times required (RQMC)	Simulation times required (MC)
[0%–3%]	$5.042e-07$	43860	
[3%–6%]	$1.273e-07$	28030	
[6%–9%]	$5.11e-08$	6054	50000
[9%–12%]	$2.833e-8$	21400	
[12%–22%]	$2.95e-9$	25170	
[22%–100%]	$4.923e-12$	49998	

From the local point of view on each tranche diagram, when the simulation times are the same, the variances of the RQMC method are much smaller than those of the MC method, which indicates that the simulation results of the RQMC method are more stable than those of the MC method when the simulation times are the same.

Particularly, in order to compare the simulation times required under the same variance of two simulation methods, we carry out spline interpolations for the variances data of the RQMC method for each subgraph in Figure 3. Without loss of generality, in each subgraph of Figure 3, we take the variances corresponding to 50000 simulation times of the MC method as an example to illustrate. At this time, the simulation times required by the RQMC method are shown in Table 2.

We can see from Table 2, for the same variances, when the total number of simulations of the MC method required is 50000, in addition to the tranche [22%–100%], simulation times of the other five tranches of the RQMC method are all far lower than 50000. Furthermore, the RQMC method can save about 25000 times on average and reduce the cost of the program running effectively.

5. Conclusion and Discussion

In this paper, a numerical algorithm based on the RQMC simulation method was designed and an empirical study was carried out to solve CDO pricing with the stochastic correlation problem of the two states under nonhomogeneous assumptions. The variances of RQMC simulation results were compared with those of the MC method from the perspective of variance changes. The results showed that the algorithm designed in this paper is more stable and reliable whether from the local view or from the global view, and it is an efficient and stable algorithm to solve CDO pricing with stochastic correlation problems under nonhomogeneous conditions, which would provide theoretical and empirical support for solving similar problems.

The algorithm in this paper is only empirically analyzed based on the Gaussian Copula model with stochastic correlations under nonhomogeneous assumptions. We point out that the algorithm can be generalized. For example, under the framework of the algorithm, the Gaussian Copula model in the algorithm can be replaced with other single-factor Copula models and the algorithm still works. Of course, for different single-factor Copula models, the implementation of the algorithm may be more complex.

In addition, the algorithm can also be extended to CDO pricing with three-state stochastic correlations under nonhomogeneous assumptions.

In the following study, we will further optimize the algorithm to improve its versatility. It is also considered to apply the numerical algorithm to the pricing of other assets in credit derivative markets under nonhomogeneity assumptions.

Data Availability

The data for the empirical study are randomly generated by MATALB code according to the algorithm in this paper. If readers need it, please contact the corresponding author for discussion.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the NSFC, under grant 11801529.

References

[1] C. Y.-H. Chen and S. Nasekin, “Quantifying systemic risk with factor copulas,” *The European Journal of Finance*, vol. 26, no. 18, pp. 1926–1947, 2020.
[2] M. Nevrla, “Systemic risk in European financial and energy sectors: dynamic factor copula approach,” *Economic Systems*, vol. 44, no. 4, Article ID 100820, 2020.
[3] X. Burtschell, J. Gregory, and J.-P. Laurent, “A comparative analysis of CDO pricing models under the factor Copula framework,” *Journal of Derivatives*, vol. 16, no. 4, pp. 9–37, 2009.
[4] X. Burtschell, J. Gregory, and J. Laurent, “Beyond the Gaussian copula: stochastic and local correlation,” *The Journal of Credit Risk*, vol. 3, no. 1, pp. 31–62, 2007.
[5] R. C. Yang, X. Z. Qin, and T. Chen, “Single factor model with mixture distributions for CDO pricing,” *Application of Statistics and Management*, vol. 28, no. 6, pp. 1082–1090, 2009.
[6] J. C. Hull, “Options,” *Futures and Other Derivatives*, Pearson Education India, Noida, India, 10th Edition, 2018.
[7] N. Morcos and T. Sayah, “Reduced basis method for the adapted mesh and Monte Carlo methods applied to an elliptic stochastic problem,” *Computational and Applied Mathematics*, vol. 38, no. 2, p. 93, 2019.
[8] T. A. Abushal, “Parametric inference of Akash distribution for Type-II censoring with analyzing of relief times of patients,” *AIMS Mathematics*, vol. 6, no. 10, pp. 10789–10801, 2021.
[9] X. Wang and I. H. Sloan, “Quasi-Monte Carlo methods in financial engineering: an equivalence principle and dimension reduction,” *Operations Research*, vol. 59, no. 1, pp. 80–95, 2011.
[10] Z. He and X. Wang, “Convergence analysis of quasi-Monte Carlo sampling for quantile and expected shortfall,” *Mathematics of Computation*, vol. 90, no. 327, pp. 303–319, 2020.

[11] E. Hintz, M. Hofert, and C. Lemieux, "Grouped normal variance mixtures," *Risks*, vol. 8, no. 4, p. 103, 2020.
[12] B. Johansson, S. Jain, and J. Montoya-Torres, "American Option Pricing with Randomized Quasi-Monte Carlo Simulations"" in *Processing of the Winter Simulation Conference*, pp. 2705–2720, IEEE, Baltimore, MD, USA, December 2010.
[13] B. A. Amal, L. Pierre, and P. Florian, "Array-RQMC for Potion Pricing under Stochastic Volatility Models," in *Processing of the Winter Simulation Conference*, pp. 440–451, Maryland, December 2019.
[14] Z. He, "Sensitivity estimation of conditional value at risk using randomized quasi-Monte Carlo," *European Journal of Operational Research*, vol. 298, no. 1, pp. 229–242, 2022.
[15] S. Qu, Y. Guo, Y. Xu, and H. Li, "A general numerical algorithm for CDO pricing based on single factor copula framework and nonhomogeneous assumptions," *Mathematical Problems in Engineering*, vol. 2022, Article ID 3802445, 6 pages, 2022.

Hindawi
Complexity
Volume 2022, Article ID 8407521, 18 pages
https://doi.org/10.1155/2022/8407521

Research Article

On the Prediction of Product Aesthetic Evaluation Based on Hesitant-Fuzzy Cognition and Neural Network

Xinying Wu,[1] **Minggang Yang**,[1] **Zishun Su**,[1,2] **and Xinxin Zhang**[3]

[1]*School of Art, Design and Media, East China University of Science and Technology, Shanghai, China*
[2]*Shanghai Business School, 2271 West Zhongshan Rd., Shanghai, China*
[3]*School of Architecture and Art Design, Hebei University of Technology, Tianjin, China*

Correspondence should be addressed to Xinying Wu; y10170069@mail.ecust.edu.cn

Received 9 January 2022; Revised 18 April 2022; Accepted 30 April 2022; Published 20 June 2022

Academic Editor: Ning (Chris) Chen

Product market competitiveness is positively influenced by the aesthetic value of product form, which is closely related to product complexity. By measuring the cognitive complexity of the product, this research establishes the relationship between the complexity and aesthetics of the product using an artificial neural network. Hence the prediction of product beauty is achieved, which guides design decisions. In this article, the complexity of product form is first measured through a combination of hesitant-fuzzy theory and information axiom. Afterward, the result is weighted by exponential entropy and dimensionally compressed. This method makes data more suitable for the prediction with small samples, obtaining an accuracy improvement of up to 40% compared with traditional approaches. Finally, the importance order of the design elements which affect morphological complexity is acquired. Results show that three of the six complexity features (element number, object intelligence, and object detail) are more significant, impacting the aesthetic feeling of product form. The method increases the attractiveness of products to customers, providing valuable design support for enterprises and designers in the early days when a new product is designed, and reducing research and development risks.

1. Introduction

In recent years, the study of aesthetic and complexity has attracted extensive attention from scholars in the fields of industrial design, psychology, and industrial engineering. There is a specific implicit correlation between aesthetic and complexity [1], where the complexity affects aesthetic feelings of people [2]. In aesthetic process, people will judge the aesthetic scale of the aesthetic object through visual cognition [3], thus, cognitive differences between the complexity of the product form, which is termed as cognitive complexity, and the objective form complexity and aesthetic evaluation are produced. The cognitive complexity can directly reflect the aesthetic degree of an aesthetic object, and too high or too low cognitive complexity will not bring a pleasant aesthetic experience [4]. However, most existing studies focus on the calculation of the complexity and beauty of the structure ontology [5] and seldom consider the complexity measurement after visual cognitive processing, which is critical for the overall aesthetic evaluation of a product and has a direct impact on user experience and preference. Therefore, research on the quantification of cognitive complexity is urgent, and how to better quantify the complexity of a product after user perception has become a key consideration for product development.

The core of product design is to meet customer needs [6]. The designers used to develop and design products relying on their own experiences and tastes, which results in problems such as incomplete cognition and unequal aesthetic information of consumers. Thus, more than 80% of the latest products will face failure in the fast-changing consumer market [7]. Suh [8] proposed the design-centric complexity theory (DCC) based on axiomatic design theory, which focuses on the study of complexity generation in the design process [9], providing theoretical support for the quantification of visual cognitive complexity. In practical applications, the process to measure users' affective cognition suffers from high complexity and uncertainty and cannot directly obtain accurate values as the DCC model requires exact values. The DCC model is limited in measuring user cognitive complexity. This study combines the DCC model with hesitant-fuzzy theory to quantify the hesitation raised in user perception to overcome this problem.

This method takes customer perceived aesthetics as the prediction index. It uses a neural network to establish a prediction model of the relationship between visual cognitive complexity and customer perceived aesthetics, which can effectively reflect the potential relationship between user perceptual aesthetics and product complexity design rules, to reduce the failure probability of new products and optimize product form design. In the process, dimension compression was adopted to handle the sample data. A good training effect was finally achieved using small sample data. The proposed method addressed the problem that users' perceptual data in traditional perceptual engineering is difficult to collect, and the amount of data is generally small, which cannot meet the requirements for machine learning.

The technical route adopted in this study is as follows. First, accurate user perceptual and cognitive needs are explored. The complexity principles affecting product modeling are collected according to relevant literature. Using the characteristic of hesitant fuzziness of user perceptual cognition, we applied the semantic difference (SD) method to evaluate user perceptual cognition. Second, a complexity calculation model of product form is established. The hesitant-fuzzy theory and the DCC model are combined to build the product form complexity model. Then, the model is used to measure the collected user perceptual data to complete the measurement of product complexity. Finally, a machine learning prediction method using a small sample is proposed. A combination of PCA algorithm and exponentially weighted entropy method is used to effectively compress the collected user perceptual data. The results show that the accuracy of the predicting model is improved by more than 40%, indicating the feasibility of the proposed model.

In summary, the main contributions and innovations of our works are as follows:

(1) In product design, the hesitant-fuzzy linguistic term set and DCC model are combined to measure the complexity after user cognitive processing, achieving a practical quantitative effect and dramatically reducing subjective factors' influence.

(2) A machine learning approach is used to develop product form beauty predictions using neural networks. A relationship between beauty and complexity is established. An exponentially weighted entropy was used to calculate the complexity principle and demonstrate a complexity index importance ranking to guide designers in the initial development of product design.

(3) A new data dimensional compression method is proposed, which overcomes the problem of small user perceptual data and difficulty in machine learning. A feasible small sample training method is constructed to improve the prediction accuracy significantly.

The rest of the article is organized as follows: in Section 2, some relevant research is introduced. In Section 3, the technical route of this study is shown. Later in Section 4, the case analysis and comparative verification are conducted. Finally, the article is concluded in Section 5.

2. Related Works

2.1. Cognitive Complex System. The cognitive complex system of the human brain has strong coupling and nonlinear characteristics, which involves the synergy of multilevel complex cognitive system [10] as is the same with visual cognition. Newell and Shaw [11], and Donderi [12] viewed that visual complexity is related to visual information acquisition, data integration, and perceptual processing, which was applied in aesthetic measurement [13].

In current researches, visual cognitive complex systems mainly focus on two aspects:

(1) the manifestation of visual complexity and

(2) the relationship between complexity and attention.

As for the first aspect, the complexity of vision is multidimensional, and it can be divided into ontology and derivative complexity [14]. Ontology complexity is the complexity of an object's structure, system, and information volume, and derivative complexity can stimulate different emotional responses in the cognitive system, which is directly affected by the complexity of the ontology. To investigate the influence of visual complexity on emotion, Berlyne and Maher [15] experimented on the complexity of product modeling. They found that the complexity can affect the arousal and pleasure of the subjects' emotions, and the complexity of emotion and modeling presents an inverted U-shaped curve. Based on the cognitive model that Berlyne proposed, Baxter [16] found that it is the complexity perceived by the human brain after cognitive processing instead of the perceptual cognition caused by product that form the direct complexity of the product.

For another aspect, visual attention, as an essential optical characteristic, plays a vital role in human visual perception [17]. When the form of a cognitive object has a medium complexity, human cognitive ability, and attention degree can reach the highest level [18]. These contribute to aesthetic recognition for users. For example, Hagerhall et al. [4] concluded that human visual cognition is more inclined to the figure under a dimension of 1.3. Sun et al. found that there is a nearly monotonous relationship between visual complexity and aesthetic expectation [19]. In the complex system research of product, the DCC model is guided by users' cognitive needs and can be used to measure the complexity of product form [8]. Compared with other evaluation and measurement methods, DCC does not need the decision-maker to determine the index weight for discrimination [6], which weakens the influence of human subjective factors. By calculating the amount of the product system information, the measurement of product complexity can be achieved.

The studies above show the research value association between visual cognitive complexity and beauty of product form. However, there are some limitations. Although DCC provides a specific theoretical regulation for designers to quantify the complexity of products, an accurate value is required to calculate, which is not available for fuzzy value calculation. While in the research of product complexity calculation, human perceptual cognition was absent, and user emotional needs were not considered. Therefore, combining the DCC model, we proposed a new method for quantifying cognitive complexity suitable in the product field: (1) Perceptual variables in the visual cognitive data acquisition link are introduced, which more fits people's actual perceptual needs increases the experimental reliability. (2) Considering the influence of cognitive hesitation fuzziness, the DCC model was combined with hesitant-fuzzy theory, enhancing the usability.

2.2. Hesitant-Fuzzy Theory. The fuzzy algorithm was proposed by Zadeh [20] to solve the problem of nonlinearity and uncertainty, which has been used widely in product design to perform fuzzy reasoning on user cognitive ambiguity [21–23]. It can establish an accurate relationship between the actual psychological intention and the product characteristics in cognitive processing. However, when measuring the complexity of product form, many uncertain factors occur. The system is random, fuzzy, and hesitant, and it is hard to determine the specific value of the index accurately. As depicted in Figure 1, in the process of perceptual cognition, the aesthetic standards of product form (complexity, order, etc.) are produced by the visual region of the human brain, and the prefrontal cortex finally makes the aesthetic decision [24]. The whole cognitive process is accompanied by the interference of hesitant and fuzzy factors. Thus the results obtained are subject to bias depending on traditional perceptual engineering measurements.

Most scholars applied fuzzy mathematical methods to quantify perceptual indicators to solve this problem accurately. Kulak and Kahraman [25] used the concept of fuzzy logic to quantify perceptual variables using affiliation functions to achieve an accurate measurement of user perception. Shen and Wang [26] proposed a combination of fuzzy language and perceptual data to deal with the fuzzy problem in decision-making. The literature [27] presented fuzzy linguistic summarization, which defined fuzzy rules and correlated the rules with users' affective needs to capture their actual perceptual needs. Although the above studies considered the fuzziness generated by user perceptions, they paid less attention to the uncertainty and hesitation raised by user perceptions in the process. In the actual measurement process, much of the information about users' perceptual cognition is challenging to accomplish quantitatively. In our interviews with users, people are found to be more likely to use verbal descriptions to evaluate indicators or decisions, which is consistent with the ambiguity of human thinking. At the same time, there is often a strong sense of hesitation and uncertainty in the user's decision-making process. The decision-maker will hesitate between multiple linguistic terms, requiring more complex linguistic terms to express the decision [28]. There are limitations to accurately quantifying fuzzy information using only the fuzzy mathematical principles. However, this can be overcome by the hesitant-fuzzy theory.

For example, Wang and Zhao [29] used a combination of hesitant-fuzzy theory and consensus models to achieve decision information integration. Similarly, the hesitant-fuzzy theory is often combined with different evaluation models for ambiguity problems analysis. Liao et al. [30] combined hesitant-fuzzy theory with the VIKOR method to make decision evaluations, and Beg and Rashid [31] extended hesitant-fuzzy linguistic decision-making to the Topsis method. In perceptual engineering, the hesitant-fuzzy theory has also been applied to quantify users' perceptual decisions. For example, Hirokawa et al. [24] introduced the hesitant-fuzzy theory in perceptual engineering to quantify users' perceptual evaluations of product styling. This shows that: (1) Hesitant-fuzzy theory is very helpful for quantifying uncertain information triggered by user perception and dealing with fuzzy problems in decision-making, which can greatly reduce the influence of subjective factors on the outcome. (2) Hesitant-fuzzy theory can be combined with a variety of methods and is more flexible. In hesitant-fuzzy theory, a language term can only correspond to one variable or index and cannot establish a mapping relationship with complex indexes, schemes, variables, and so on. Therefore, based on hesitant-fuzzy language, Rodriguez et al. [32] proposed hesitant-fuzzy linguistic term sets (HFLTSs) to solve the cognitive fuzziness caused by multifactor hesitation. When users are hesitant about multiple language terms, HFLTSs can make the qualitative judgment more accurate and help decision-makers make effective decisions. Therefore, this article uses the HFLTSs to measure users' perceptual cognition.

Moreover, in product design, the research on the combination of fuzzy theory and the DCC model is still absent. The DCC model requires a definite value to calculate. At the same time, hesitant-fuzzy theory can make users' evaluation of indicators accurate and meet the calculation requirements of the DCC model. So, we combined the DCC model with hesitant-fuzzy theory. The proposed method solved the limitations of DCC theory on the one hand.

On the other hand, the problem of users' cognitive hesitation fuzziness is addressed. Compared with the research on single users' fuzziness, our proposed method is more comprehensive and objective, despite some shortcomings such as the difficulty of collecting data. Therefore, it is necessary to study the small sample prediction method in the follow-up research.

2.3. Intelligent Beauty Evaluation. Artificial intelligence is extensively used in various fields with the breakthrough of technology. The field of aesthetics is different from other

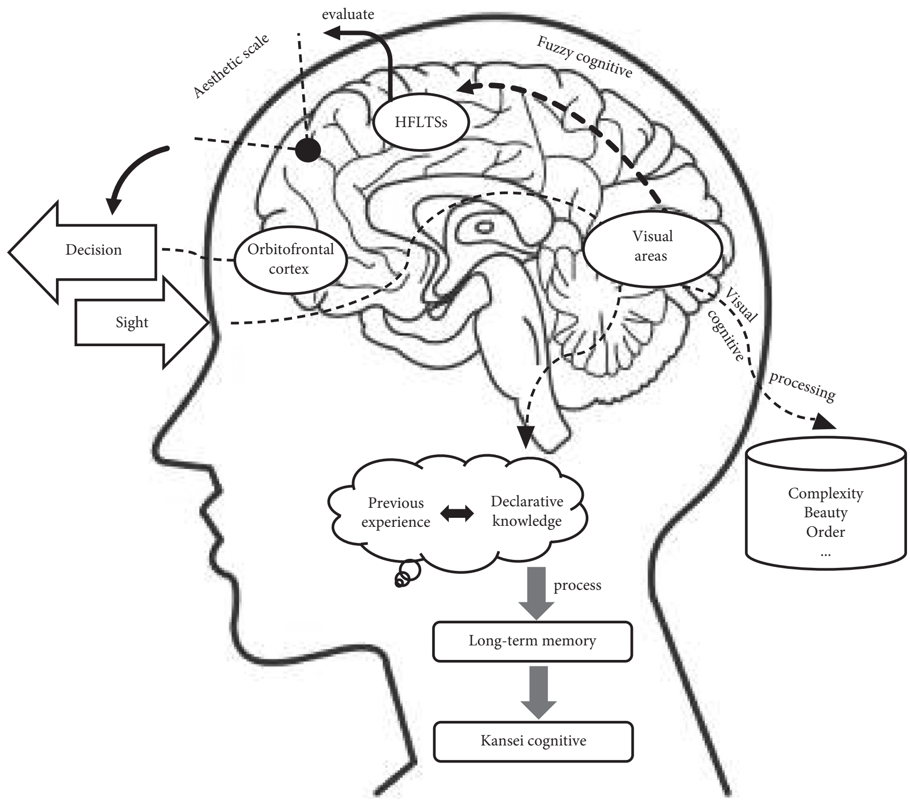


Figure 1: The decision-making process of the human brain after hesitant and fuzzy cognition.

fields because it needs to combine psychology and sociology with exploring human brain cognition. At present, aesthetic sense has become the core of human-computer interaction. The analysis and calculation of visual aesthetic models have been widely concerned [33]. A large number of studies have been conducted on image aesthetic quality evaluation [34], including web aesthetic measurement [35], fabric aesthetic prediction [36], and human facial aesthetic evaluation [37] through ANN. These studies have shown the ability of artificial intelligence to make decisions by imitating human vision and aesthetics.

The intelligent aesthetic assessment focuses on image recognition and classification problems. The research on the aesthetic perception of product form after nonlinear visual processing is insufficient, and it still stays in the stage of calculating product form beauty [38]. Based on human aesthetic preference and design aesthetics, Wong and Low [39] established a relationship between visual attention and visual aesthetics, and they improved the classification effect by extracting salient regional features. Based on Wong's extraction of salient features, Wang et al. [40] proposed an image aesthetic classifier through a machine learning method to evaluate image aesthetics. In addition, Zhang et al. [41] exploited the supervised learning method to obtain a judgment model to predict consumers' perceived aesthetics under the measurement of aesthetic principles. Because the aesthetic size of product form is affected by the subjective aesthetic of users, this prediction process is nonlinear and inconsistent. Thus, there is a tremendous technical difference between the product form and image aesthetic prediction. The image aesthetic evaluation framework cannot be fully applied to the product form aesthetic evaluation.

Considering the guiding of consumers' perceptual cognition in the prediction of product aesthetic feeling, an ANN evaluation framework for visual aesthetics of product form is proposed according to the optical characteristics of product form from the perspective of consumers. Due to difficult data collection and insufficient samples in consumer perceptual cognition surveys, it is challenging to achieve high accuracy using traditional machine learning methods. To handle the problem, this article proposed a feature dimension compression method to improve the prediction accuracy of the training model. Finally, a high-precision perceptual model describing the relationship between designers and consumers is established to provide a valuable product design paradigm.

3. Methods Overview

Based on the related work introduced above, the obtained cognition is defuzzified. The results are used to establish a prediction model for measuring the aesthetic feeling of product form. The research route is shown in Figure 2.

3.1. Computation of Visual Cognitive Complexity

3.1.1. Cognitive Complexity. The DCC theory measures the complexity of a system from the perspective of functional requirements. It translates the complexity of the design

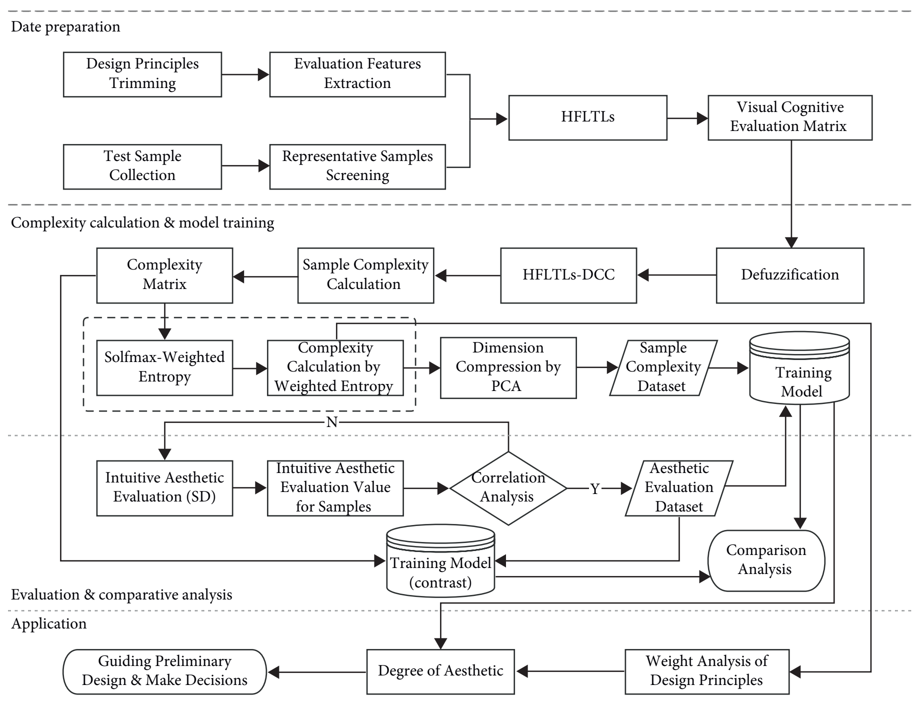


FIGURE 2: Research route of visual cognitive aesthetic prediction.

system into the probability of achieving functional requirements. It obtains the amount of complexity information that the product system conveys by calculating the conversion probability of emotional cognition. Therefore, according to the DCC theory, the complexity information of a user's visual cognition can be expressed as

$$I_p = -\log_2 p_s = \log_2\left(\frac{1}{p_s}\right), \quad (1)$$

where p_s denotes the realization probability of cognitive field F_s. The higher the probability F_s, the lower the system complexity degree, and vice versa. Denoting the probability density function of the system as $P_x(eFR)$, the realization probability of the designing scope in a system F_s is formulated as follows:

$$p_s = \int_{dl}^{du} P_x(eFR)d(eFR). \quad (2)$$

In equation (2), du is the upper limit of the design range and dl is the lower limit of the design range. While in formula (1), I_p is the information quantity of product-cognitive system. The public scope is the overlapping area of the design-cognitive range and system-cognitive range. According to the principle of information axiom, equation (3) can be obtained, where A_{cr} is the area of the cognitive common range, R_{cc} is the cognitive common range, and R_{cs} is the cognitive system range.

$$p_s = \frac{R_{cc}}{R_{cs}} = A_{cr}. \quad (3)$$

The complexity of the design scheme can be evaluated by calculating the common area following the DCC theory. Therefore, this study determines the complexity of the design system by calculating the public area and obtains the complexity of the product system after visual cognitive processing, as shown in Figure 3.

In Figure 3, the range of the system is the range of the actual cognitive system and the range of objective information, which is determined by the specific attributes of system. E-FR denotes the user's emotional needs, and it is a continuous variable. As the design goal, the design range represents the designer's demand for the design plan. The overlapping part of the design range and the system range is the public range, which means the ability of the design plan to meet the needs of the project. According to logical analysis, the larger the area of the public area, the lower the system complexity, and vice versa. Therefore, according to equation (3), the calculation formula for complexity can be expressed as

$$\mathscr{C} = \frac{R_{cc}}{R_{de} \cap R_{cc}}, \quad (4)$$

where R_{de} is the design range.

3.1.2. Hesitant-Fuzzy Information Axiom. According to the semantic level, the questionnaire is divided into specific grades (very low, low, average, high, very high) and corresponding scores $(1, 2, 3, 4, 5)$. However, due to the fuzziness of cognition, there are fuzziness and hesitation in the process that users participate in the evaluation. For example, when the user evaluation score is 3, there may be two ranges of actual psychological perception: $2-3$ or $3-4$. The numerical scales cannot accurately reflect the user preferences, and it is not easy to calculate the information quantitatively.

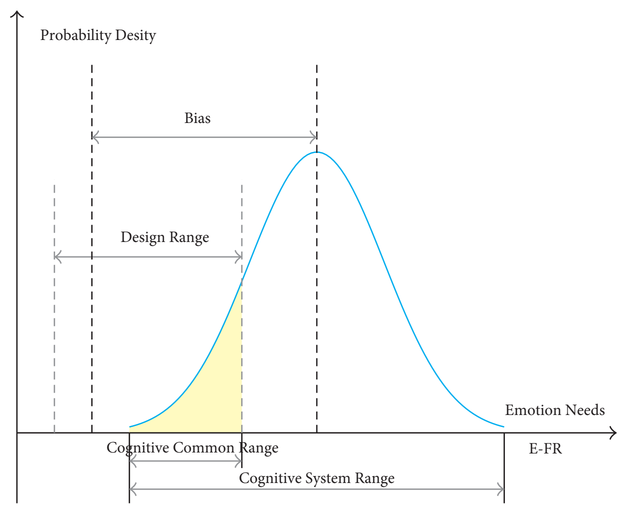


Figure 3: Schematic diagram of the cognitive common range and cognitive system range.

As can be seen, the product design system pays attention to the intuitive feelings of the objects in the evaluation process, which leads to the randomness of the evaluation results.

Therefore, the method of hesitant-fuzzy mathematics is introduced in the article. By defuzzifying the user evaluation with the hesitant-fuzzy linguistic term set [42], each scale obtained by the subject's score can be determined, and the different evaluation indicators of the sample can be calculated. Meanwhile, based on the information axiom design, the ability of each sample to meet different design requirements can be determined.

According to the theory of hesitant-fuzzy linguistic term set, let $A = \{A_1, A_2, \ldots, A_n\}$ be an ordered language term set. The set contains odd language terms with symmetrical meanings. In this study, the language set is divided into five language terms: very low (VL), low (L), middle (M), high (H), and very high (VH), i.e., $A = \{A_1\colon VL, A_2\colon L, A_3\colon M, A_4\colon H, A_5\colon VH\}$. Given $A_\alpha, A_\beta, \lambda > 0$, there exist the following algorithms according to the literature [43]:

$$\begin{aligned} A_\alpha \oplus A_\beta &= A_{\alpha+\beta},\\ \lambda A_\alpha &= A_{\lambda\alpha},\\ (\lambda_1+\lambda_2)A_\alpha &= \lambda_1 A_\alpha \oplus \lambda_2 A_\alpha,\\ \lambda\left(A_\alpha + A_\beta\right) &= \lambda A_\alpha \oplus \lambda A_\beta. \end{aligned} \tag{5}$$

In this study, the algorithms are extended to improve the accuracy of decision-making using concepts of set as follows:

Definition 1. Let $A = \{A_1, A_2, \ldots, A_n\}$ be an ordered language term set, and $\mathbf{H}_s = \{h_s(x) \mid s \in \text{subset}(A), x \in X\}$ be a hesitant-fuzzy linguistic term set on domain X, which represents the set of all possible subordinate fuzzy language terms of an object.

Let $A = \{A_1\colon VL, A_2\colon L, A_3\colon M, A_4\colon H, A_5\colon VH\}$ be the fuzzy evaluation of product feature complexity. Then, $\mathbf{H}_s = \{h_s(1) = (A_2, A_3), h_s(2) = (A_3, A_4)\}$ of decision-maker's evaluation of two products complexity is a set of hesitant-fuzzy linguistic terms.

To evaluate different projects in the domain, an overall algorithm considering the evaluation of different decision makers is developed.

Definition 2. Suppose the hesitant-fuzzy linguistic term set $\mathbf{H}_s = \cup_{i=1}^{n} \mathbf{H}_s^i, i = [1, n]$ on domain X, and n is the number of decision makers. $\mathbf{H}_s^i = \{h_s^i(x) | s \in \text{subset}(A), x \in X, i \in [1, n]\}$ represents the hesitant-fuzzy linguistic evaluation of each decision-maker i. $A = \{A_1, A_2, \ldots, A_n\}$ is the hesitant-fuzzy semantics, and the algorithm is defined as follows:

$$\begin{aligned} \mathbf{H}_s^i + \mathbf{H}_s^j &= \left\{h_s(x) | h_s^i(x) + h_s^j(x)\right\},\\ \alpha\mathbf{H}_s^i &= \left\{h_s(x) | \alpha h_s^i(x)\right\},\\ \alpha\mathbf{H}_s^i + \beta\mathbf{H}_s^j &= \left\{h_s(x) | \alpha h_s^i(x) + \beta h_s^j(x)\right., \end{aligned} \tag{6}$$

where the symbol $\cup$ represents the sum of the number of ambiguous semantic elements. According to Definition 1, we have

$$\begin{aligned} \mathbf{H}_s &= \mathbf{H}_s^1 + \mathbf{H}_s^2,\\ \mathbf{H}_s^1 &= \{h_s(1) | (A_2, A_3)\},\\ \mathbf{H}_s^2 &= \{h_s(1) | (A_3, A_4)\}. \end{aligned} \tag{7}$$

Therefore,

$$\mathbf{H}_s^1 + \mathbf{H}_s^2 = \{h_s(1) | (A_2, 2A_3, A_4)\}. \tag{8}$$

3.1.3. Defuzzification Calculation of Hesitation Fuzziness. According to Section 3.1.2, the user's hesitant-fuzzy evaluation matrix $\mathbf{H}_s$ for product complexity can be obtained. In fuzzy control theory, the precise value transformation of fuzzy behavior is called antifuzzy. Since the evaluation matrix counts all possible evaluation sets, the defuzzification calculation is performed by seeking the expectation.

Definition 3. Suppose a fuzzy hesitation evaluation matrix $\mathbf{A}$ that can be expressed as

$$\mathbf{H}_s = \mathbf{F}_s \odot \mathbf{A}. \tag{9}$$

The symbol $\odot$ in equation (9) represents the product of two vectors by element position, and $\mathbf{A}$ represents the hesitant-fuzzy linguistic term set matrix. Then, $\mathbf{F}_s$ is the characteristic matrix of the fuzzy hesitant evaluation matrix $\mathbf{H}_s$, which represents the frequency of occurrence of the corresponding hesitant-fuzzy linguistic terms.

Denote the symbol $\text{deF}(X)$ as the defuzzification operation to solve the vector X. Then, according to Definition 3, we have

$$\begin{aligned} deF\left(H_s\right) &= deF\left(\mathbf{F}_s \odot \mathbf{A}\right)\\ &= \frac{1}{s}\sum_{i \in s} \mathrm{F}_i. \end{aligned} \tag{10}$$

The formula shows that the defuzzification of $\mathbf{H}_s$ is obtained by calculating the expectation of its eigenvector.

3.1.4. Complexity Calculation. The user's subjective evaluation is hesitant and vague. Therefore, by converting the personal evaluation into a hesitant-fuzzy semantic variable, the subjects' actual psychological potential evaluation value can be obtained more accurately. Through this method, the user's hesitant-fuzzy evaluation is transformed into hesitant-fuzzy semantics, and the membership function of hesitant-fuzzy semantics is obtained. According to the definition of the information axiom, the hesitant-fuzzy evaluation is exploited to transform the range of user emotional needs. Considering the characteristics of fuzzy mathematics, we can transform the design range into a trapezoidal area, as shown in Figure 4.

The hesitant-fuzzy value of the user's evaluation of product features can be obtained through the fuzzy hesitant language term set in equations (6) and (10). Assume that the hesitant-fuzzy score of the target is 3.26. Through this score, the hesitant-fuzzy complexity bounded can be obtained based on the information axiom, indicating the area of the shadow region in the figure. The fuzzy complexity is calculated according to different feature evaluations of the sample, and the feature complexity matrix of sample i is obtained by

$$\mathbf{C}_i = \left[C_{i,1}, C_{i,2}, C_{i,3}, \ldots, C_{i,n}\right], 1 \le n \le N. \quad (11)$$

The specific complexity calculation consists of the following steps:

(1) Determine the complexity evaluation index.

(2) Establish the hesitant-fuzzy cognitive matrix (HFCM) of the user evaluation.

(3) Calculate the HFCM.

(4) Normalize and calculate the complexity matrix of different features for all samples.

In Step 1, any element and color composition can trigger a psychological reaction after visual stimulation. The complexity of visual stimulation includes the number of elements and the degree of similarity and unity [44]. Design complexity is critical to the complexity of product form. It has always been the focus of research in the field of design. The principle of design complexity is defined by Gestalt psychology [45], visual complexity measurement [12], information reception [46], etc. It consists of design complexity [18], the quantity of objects, irregularity of objects, dissimilarity of objects, detail of objects, asymmetry of object arrangement, and irregularity of object arrangement. Through the analysis of the stimulus shape and the consumer language, the key components of the design complexity principle include the number of elements, the irregularity of object, the dissimilarity of object, the detail of object, the asymmetry of element arrangement, and the irregularity of element arrangement, which are taken as the characteristic induces of complexity, and described in Table 1.

In Step 2, the questionnaire is designed according to the six key components of the design complexity principles. The Likert scale is used to evaluate the sample complexity. The

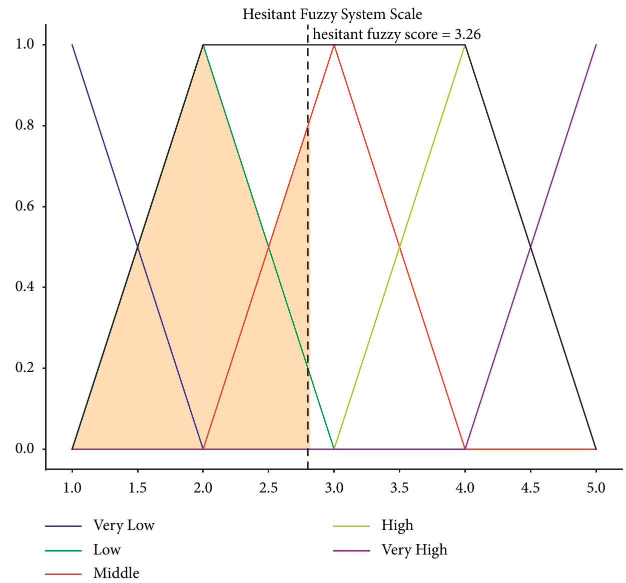


Figure 4: Hesitant-fuzzy common range diagram.

semantics of sample morphology are transformed into corresponding semantic variables according to the concept and complexity of the fuzzy linguistic term set. Meanwhile, the fuzzy value is used to express the evaluation value of the feature degree. The language term set of $S = \{S_1\colon VL, S_2\colon L, S_3\colon M, S_4\colon H, S_5\colon VH\}$ is used to evaluate the sensibility of the sample. In this way, the user's scoring matrix $\mathbf{S}_k = |s_{ij}^k|, i \in [1, M] j \in [1, N]$ for the complex features of sample k is obtained, where M is the number of subjects; N is the number of features, and K is the number of samples.

The characteristics of the complexity described above are denoted as: EN (Element Number), OI (Object Irregularity), OD (Object Dissimilarity), OT (Object deTail), AA (Arrangement Asymmetry), and AI (Arrangement Irregularity). Then, the matrix can be expressed as

$$\begin{array}{c} \begin{array}{cccccc} \mathrm{EN} & \mathrm{OI} & \mathrm{OD} & \mathrm{OT} & \mathrm{AA} & \mathrm{AI} \end{array} \\ \mathbf{S}_k = \begin{vmatrix} s_{11}^{(k)} & s_{12}^{(k)} & s_{13}^{(k)} & s_{14}^{(k)} & s_{15}^{(k)} & s_{16}^{(k)} \\ s_{21}^{(k)} & s_{22}^{(k)} & s_{23}^{(k)} & s_{24}^{(k)} & s_{25}^{(k)} & s_{26}^{(k)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{m1}^{(k)} & s_{m2}^{(k)} & s_{m3}^{(k)} & s_{m4}^{(k)} & s_{m5}^{(k)} & s_{m6}^{(k)} \end{vmatrix}. \end{array} \quad (12)$$

Each row represents a user's hesitant-fuzzy score on the sample in the matrix. S_k is the scoring matrix of a sample k by user m. $s_{mn}^{(k)}$ represents the intuitive evaluation of user m for feature n of sample k.

In Step 3, S_k is summed by column according to the hesitant-fuzzy linguistic calculation criterion expressed by equation (6). Then, the HFCM of feature n of the samples for the consumer is obtained:

$$R_n^{(k)} = \sum_{i=1}^{m} s_{mn}^{(k)}. \quad (13)$$

Given the hesitant-fuzzy linguistic term set matrix $A = \left\{A_1, A_2, \ldots, A_j\right\}$, the above formula can be expressed as

Table 1: Complexity induces and their evaluation principles.

Complexity index	Evaluation principles
Element Number	The number of main elements in product shape. It mainly refers to the number of constituent structures and components. When the shape contains more elements, the complexity is higher.
Object Irregularity	The overall product modeling has no regularity and order, does not have a unified coordination, and does not meet the Gestalt principle.
Object Dissimilarity	There is no similarity between the structural forms of product modeling (including modeling lines, lines and curves). The direction of the modeling line is not uniform and similar, and the product material and texture are not similar.
Object Detail	The degree of detail and decoration of the product. For example, decorative lines and decorative components, as well as the use of details and textures in product modeling design. When there are less details in product modeling, the complexity of design is greater.
Arrangement Asymmetry	The constituent elements (main functional components) of the product form an asymmetric arrangement. When there is no symmetrical design, the complexity is greater.
Arrangement Irregularity	The constituent elements (main functional components) of the product form an irregular arrangement and have no order lines. When the product space is randomly distributed, it has higher design complexity.

$$\mathbf{R}_{EN}^{(k)} = \mathbf{F}_{EN}^{(k)} \odot \mathbf{A}, \tag{14}$$

where the symbol $\odot$ denotes the product of two vectors by element indices. Thus, an HFCM can be implied by $\mathbf{F}$, if $\mathbf{A}$ is fixed.

Finally, in Step 4, $F_n^{(k)}$ is normalized, and its mean value is calculated according to the weight of the hesitant-fuzzy linguistic terms which affiliated.

$$M_n^{(k)} = \overline{F_n^{(k)}} \cdot W^T = \frac{\sum_{i=n}^{m} \left(s_{i,n}^{(k)} * w_i \right)}{\sum_{i=n}^{m} s_{i,n}^{(k)}}. \tag{15}$$

Then the complexity degree $C_n^{(k)}$ of feature n for the sample is calculated following the method described in Section 3.1.3. The rest can be deduced by analogy. Based on this, the complexity degree matrix $\mathbf{C}_N$ containing the complexity degree of all the features is obtained.

3.2. Exponential Weighted Entropy Complexity Calculation. After the user's cognitive complexity is calculated, there is noise in the data and should be eliminated according to the needs of neural network prediction. The entropy weight method determines the objective weight according to the index variability. This method has been widely used in engineering technology, social economy, and other fields. The smaller the information entropy of an index, the greater the dispersion of the index value and the more information it provides, so the more significant the weight in the comprehensive evaluation, and vice versa. To investigate the feature weights that affect the thorough evaluation of samples, an improved entropy weight model suitable for the data characteristics of this study is proposed.

Following the method described in Section 3.1.3, the fuzzy evaluation matrix $\mathbf{C}_N = [C_1, C_2, C_3, \ldots, C_n], 1 \le n \le N$ of consumer hesitation is obtained. C_n is a column vector that represents the evaluation of different samples on feature n. The steps of feature weight calculation are as follows:

(1) Use the maximum-minimization principle to normalize the evaluation matrix $\mathbf{C}_n$ by column to obtain the normalized complexity matrix C_n':

$$\mathbf{C}_N{}' = \frac{\mathbf{C}_n - \min(\mathbf{C}_n)}{\max(\mathbf{C}_n) - \min(\mathbf{C}_n)} \Big|_{\text{column}}. \tag{16}$$

(2) Calculate each feature's proportion of the features for the sample by column:

$$P_N = \frac{\mathbf{C}_N{}'}{\sum \mathbf{C}_N{}'} \Big|_{\text{column}}. \tag{17}$$

Thus, the weight matrix $P_{K\times N}$ with a dimension of $K \times N$ is obtained:

$$P_{K\times N} = \left| p_{ij} \right|, i \in [1, K], j \in [1, N]. \tag{18}$$

(3) Based on the complexity matrix $\mathbf{C}_N$, the weight matrix $p_{i,j}$ of feature n of sample k can be obtained, and the entropy of each feature can be calculated:

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{K} p_{ij} \ln\left(p_{ij}\right), j \in [1, N]. \tag{19}$$

(4) Use the exponential weight function to calculate the weight of e_j. The calculation is shown as follows:

$$w_j = \frac{e^{x_j}}{\sum_{j=1}^{n} e^{x_j}}. \tag{20}$$

In the formula, $\mathbf{x} = [x_1, x_2, \ldots, x_n]$. Following this method, the values close to each other can be separated better, hence features with higher aesthetic impact can be screened out and higher prediction accuracy is obtained.

(5) Finally, the weighted complexity of each sample is calculated by using the feature weights.

$$\mathbf{C} = \mathbf{W} \cdot \mathbf{C}_N. \tag{21}$$

Following the above steps, the sample complexity is calculated, where $\mathbf{W} = |\mathrm{w}_j|, j \in [1, N]$.

3.3. Dimension Compression of Visual Cognitive Complexity. To guarantee the reliability of results, multi-dimensional information on research objectives is usually collected in data analysis. Although there is a specific correlation between the dimensions, they cannot be analyzed independently. Otherwise, the research process will be affected by the loss of data information, leading to a bad deviation of conclusions. The PCA proposed by Turk and Pentlad [47] can solve the above problems. Based on K-L transformation (Karhunen-Loeve Transform), PCA projects data from high-dimensional space to low-dimensional space, saving the most critical K dimensions. These K dimensions with orthogonal characteristics are called principal components.

Since neural network training requires a large amount of data to achieve high accuracy, the amount of data will increase exponentially as the number of features increases. However, the samples in the test set are insufficient and difficult to collect. In this case, the amount of data is always small, resulting in the low accuracy of the training model. In this case, the PCA algorithm is adopted to reduce data dimension to train the neural network with a small amount of data. The specific steps are as follows:

(1) Perform row-column conversion on the user complexity evaluation samples to generate matrix X with a dimension of $n \times m$, where n is the number of sample features, and m is the number of samples.

(2) Normalize X with zero-mean operation.

(3) Calculate the covariance matrix $1/nX^{*}(X^{*})^{T}$ and eigenvectors of X^{*} by using the eigenvalue decomposition method (EVD) for singular matrix.

(4) Rank the eigenvalues by size, the first values and the corresponding eigenvectors are selected to form the characteristic matrix P.

(5) Map X to the new vector space based on P:

$$X' = PX, \tag{22}$$

where X' denotes the new date after dimension compression, and it makes up the training data set for the subsequent neural network.

3.4. Artificial Neural Network. Neural networks can solve complex problems without explicit models, which are used to investigate the relationship between product complexity and aesthetic degree and predict the aesthetic degree. As shown in Figure 5, an ANN contains multiple artificial neurons divided into the input, hidden, and output layers. Specifically, the input layer is responsible for receiving signals. The hidden layer is responsible for processing and integrating the received signals. Finally, the results are achieved in the output layer.

After the input passes through these layers, the regression or classification result can be obtained. The neural network continuously uses the training data for parameter adjustment. After training with a large number of data, the optimal weight of every neural is finally fitted. At this moment, the neural network achieves the best accuracy for data prediction. Since this study uses a small number of sample data, the over-fitting problem is easy to occur in the training process. We adopted the dropout technique in this study to handle this problem, and the method will be introduced below.

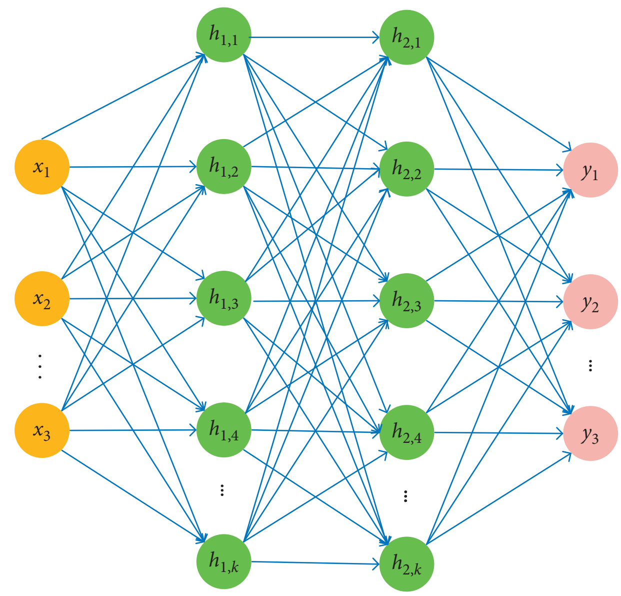


Figure 5: Artificial neural network structure.

3.5. Establishing the Cognitive Space of Form Aesthetics. In order to obtain an accurate aesthetic evaluation of users, five-order SD method is adopted to launch the questionnaire. In our existing research [48], we summarized and sorted out the aesthetic principles in the product field, combining the modern product aesthetics research theory, and obtained 9 aesthetic principles preliminarily. According to the needs of this study, the 9 aesthetic principles are reduced by the fuzzy-delphi method (FDM), and finally top 6 principles that can most affect aesthetic evaluation are determined, i.e., unity (U), rhythm (r), simplicity (S), order (O), comfortable(C), and harmonize (H). Latter, the aesthetic evaluation is estimated using a linear weight method. For instance, assume the aesthetic evaluation of the ith subject about the jth sample is denoted by $\mathbf{A}_i^j = [U_i^j, R_i^j, S_i^j, O_i^j, C_i^j, H_i^j]$, where $i = 1, 2, \ldots, m; j = 1, 2, \ldots, n.$ Thus the aesthetic evaluation of a sample can be expressed as

$$E_i^j = \frac{\sum_{n=1}^{N} \mathbf{A}_i^j}{N}, \tag{23}$$

where $N = 6$ denotes the number of principles (mentioned above) that are considered. Finally, a sample aesthetic evaluation matrix is obtained, which provides data support for neural network prediction.

4. Case Study

As a product that frequently interacts with people in life, the capsule coffee machine has a solid emotional connection with the public, which is more likely to arouse people's aesthetic resonance. Designers need to consider the structural level to provide users with emotional demand transformation. Therefore, the capsule coffee machine was

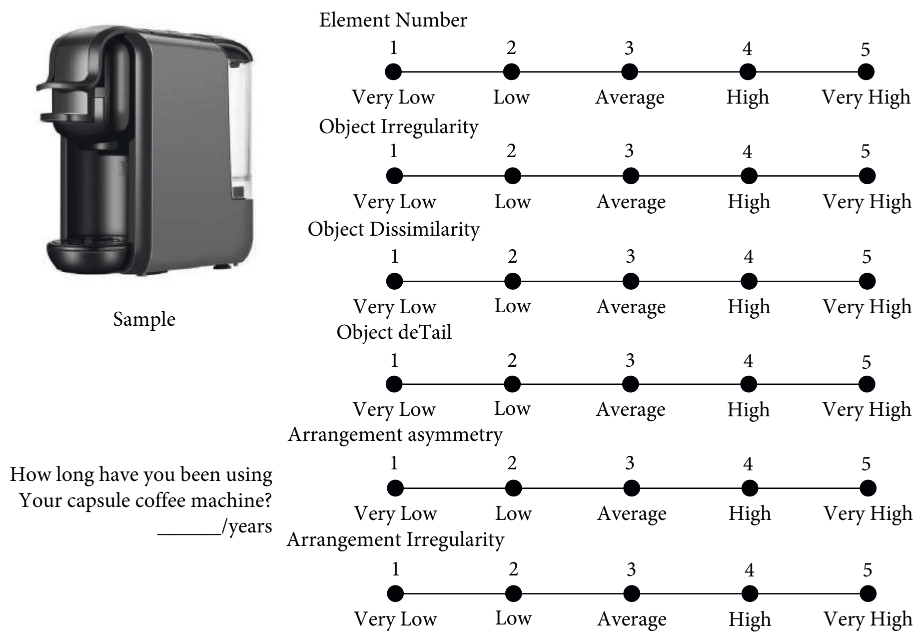


Figure 6: Questionnaire format used in the research.

selected as the test sample for the visual cognition experiment. The experiment consists of the following steps.

4.1. Samples Collection. There are 2500 pictures collected through the Internet, home appliance market, newspapers, and magazines. Six hundred test pictures were obtained after preliminary screening, which process deletes the duplicate and vague ones. The experts screened 600 images and got 96 representative samples later, as shown in Appendix 5. This study mainly focuses on the shape of capsule coffee machines; thus, the influence of other dimensions on vision is eliminated. In the process of the subjects are screened, young subjects are preferred for the following reasons.

(1) According to the regional culture and dietary habits, coffee audiences are concentrated in young customer groups.
(2) Capsule coffee machine is a fashionable household product, which is widely used by young users.

At last, 30 questionnaires were collected, and the format is shown in Figure 6.

4.2. Data Preprocessing. Once the questionnaires were obtained, we screened the valid questionnaires according to the following criteria.

(1) The participants had the experience of using capsule coffee machine.
(2) No regular filling (70% of the answers are the same).
(3) The questionnaire is complete without missing options.
(4) The response time of the questionnaire is valid (the response time should be more than 10 minutes).

After eliminating the invalid questionnaires, we collected 23 valid questionnaires. The questionnaire recovery rate was 76.7%, which was in line with the recovery rate standard of the research questionnaire [49]. As a summary, the characteristics of valid questionnaire samples are shown in Table 2:

As can be seen, the summary characteristics of Table 2 are as follows.

(1) The age of the respondents is mainly young, which meets the needs of the experiment.
(2) In the samples, industrial design students and product designers are in the majority, who have good aesthetic knowledge.
(3) The ratio of men to women is average.

4.3. Data Processing. This section exploited the hesitant-fuzzy information axiom to process the data. The complexity of consumers on different characteristics of the sample set was measured. Next, the feature complexity matrix was processed by the exponentially weighted entropy method described in Section 3.2 to obtain the complexity weights of different features. Meanwhile, the complexity evaluation result of the sample was obtained. Finally, the feature complexity matrix was analyzed by PCA to reduce the dimension of the data samples. The artificial neural network was constructed and trained with the data with a reduced size. In this way, the accuracy of the model was improved, and the impact of different characteristics on aesthetic evaluation was determined.

To illustrate the effectiveness of the proposed feature compression method, two data sets, raw data after PCA and raw data processed by the feature compression method above, are trained with ANN individually, comparison

Table 2: Statistics of valid questionnaire objects.

Feature	Option	Amount	Ratio (%)
Gender	Male	11	47.83
	Female	12	52.17
Age	18–25	8	34.78
	26–30	9	39.13
	31–40	6	26.09
Occupation	Business English	2	8.70
	Me Media	4	17.39
	Foreign Trade	2	8.70
	Student	5	21.74
	Product designer	3	13.04
	E-commerce salesperson	4	17.39
	Manufacturing market personnel	3	13.04
Using experience (year)	<0.5	4	17.39
	0.5–1	10	43.48
	1–2	4	17.39
	≥2	5	21.74

results of the convergence curve and the error curve are achieved at last.

4.4. Hesitant-Fuzzy Evaluation Matrix. All evaluation tables' feature domains and scoring domains were extracted separately, integrated, and processed. The obtained hesitant-fuzzy cognition matrix is shown in Table 3.

Each cell $C_{i,j}$ represents the hesitant-fuzzy score of the subject i for the sample j, and the order is EN, OI, OD, OT, AA, AI.

4.5. Visual Cognitive Complexity Calculation

(1) Calculate the Fuzzy Evaluation Matrix and Analyze the Reliability. Dehesitating fuzzy calculation is performed in Table 3 according to equation (10). The hesitant-fuzzy evaluation matrix $\widehat{C}_{i,j}$ of user i on sample j is shown in Table 4.

The reliability of the evaluation matrix is analyzed, and the analysis results are listed in Table 5.

The results show that the evaluation is reliable and can be used for subsequent analysis.

(2) Calculate the Complexity Matrix. Firstly, the complexity of each feature of the sample is obtained by the quantization method described in Section 3.1.4. Take the complexity of the element of sample 1, i.e., $C_{EN}^{(1)}$, as an example. According to the questionnaires, $s_{11}^{(1)} = (A_2, A_3)$. The following result is obtained by summing by column.

$$\begin{aligned} \mathrm{R}_{EN}^{(1)} &= \sum_{i=1}^{m} s_{i1}^{(1)}, \\ &= \left(5A_1, 8A_2, 23A_3, 8A_4, 2A_5\right), \\ &= (5, 8, 23, 8, 2) \odot \left(A_1, A_2, A_3, A_4, A_5\right). \end{aligned} \tag{24}$$

Thus, $\mathbf{F}_{EN}^{(1)} = (5, 8, 23, 8, 2)$.

Then, $\mathbf{F}_{EN}^{(1)}$ is normalized, and the mean value is calculated according to the weight of the fuzzy language terms which is affiliated.

$$\begin{aligned} M_n^{(k)} &= \overline{F_n^{(k)}} \cdot W^T, \\ &= \frac{\sum_{i=n}^{m}\left(s_{i,n}^{(k)} * w_i\right)}{\sum_{i=n}^{m} s_{i,n}^{(k)}}, \\ &= [0.11, 0.17, 0.5, 0.17, 0.04] * [1, 2, 3, 4, 5]^T, \\ &= 2.8696. \end{aligned} \tag{25}$$

Finally, the value of $C_{EN}^{(1)}$ is calculated following equation (14), and the result is 0.548771.

Similarly, the complexity matrix $\mathbf{C}_N$ of all subjects about each feature of all samples is calculated, where $N \in \{EN, OI, OD, OT, AA, AI\}$. The result is listed in Table 6.

(3) Calculate the Characteristic Weight of the Complexity Matrix. According to the complexity matrix $\mathbf{C}_N$, the weight matrix P_{01} of the characteristic EN of sample 1 can be obtained and the entropy value of each feature is calculated according to equations (16)–(19), and the result is shown in Table 7.

The weight w_j of each feature is calculated by equation (20), and the calculation result is shown in Table 8.

According to the results in the table, the features EN, OI, OT, and $O\ D$ have a high impact, and the weight of these four features accounts for more than 82% of the whole. Also, there is little difference in the weight of EN, OI, and OT features, so more design consideration should be paid to these three features in the early stage of product design.

(4) Calculate the Complexity of the Test Sample. According to the characteristic weight calculation shown in equation (21) and the weight vector w_j obtained in the last step, the

Table 3: Questionnaire hesitant-fuzzy cognitive matrix.

Subject	C_1	C_2	C_3	…	C_{96}
Sample Features	EN OI OD OT AA AI	EN OI OD OT AA AI	EN OI OD OT AA AI	…	EN OI OD OT AA AI
1	{3, 4}{1, 2}{3, 4} {3, 4}{1, 2}{3, 4}	{2}{3, 4}{2, 3} {2}{3, 4}{2, 3}	{3}{3, 4}{3, 4} {2}{2}{4}	…	{2}{3, 4}{1, 2} {1}{2, 3}{1}
2	{3, 4}{1, 2}{3, 4} {2}{1, 2}{3, 4}	{2}{3, 4}{2, 3} {1, 2}{1, 2}{2, 3}	{4}{3, 4}{2} {3}{1, 2}{1, 2}	…	{4}{3, 4}{2} {3}{1, 2}{1, 2}
3	{1}{1}{1, 2} {1, 2}{1}{1}	{1}{1}{1, 2} {1}{1}{1}	{2}{1}{2, 3} {1, 2}{1}{1, 2}	…	{1, 2}{2, 3}{2, 3} {1, 2}{1}{1, 2}
4	{3, 4}{2}{3, 4} {4}{1, 2}{2}	{2}{2, 3}{3} {1, 2}{1, 2}{2}	{4, 5}{3}{3} {3, 4}{1, 2}{2, 3}	…	{4, 5}{2, 3}{4} {3, 4}{2, 3}{3}
5	{3}{3}{3, 4} {2, 3}{3, 4}{3}	{2, 3}{2, 3}{3} {4, 5}{3, 4}{3}	{3, 4}{3}{3, 4} {3, 4}{3, 4}{4}	…	{2}{2, 3}{2, 3} {1, 2}{2, 3}{2, 3}
6	{1, 2}{2, 3}{3} {3, 4}{1, 2}{2, 3}	{1, 2}{3}{3} {2, 3}{2, 3}{3, 4}	{4, 5}{3}{2, 3} {4, 5}{4, 5}{4}	…	{4, 5}{2, 3}{4} {3, 4}{2, 3}{3}
7	{3, 4}{3}{2, 3} {4}{3, 4}{4, 5}	{3, 4}{3}{3, 4} {4}{4}{4}	{2, 3}{3}{4} {3, 4}{3, 4}{3, 4}	…	{4, 5}{4}{5} {5}{5}{5}
8	{2, 3}{2}{2} {2, 3}{2}{1, 2}	{2}{1, 2}{1} {1}{1}{1}	{4}{2, 3}{3} {3, 4}{3}{2}	…	{4, 5}{3, 4}{4, 5} {2}{2, 3}{2, 3}
⋮	⋮	⋮	⋮	⋱	⋮
23	{1, 2}{3, 4}{3, 4} {2}{2}{3, 4}	{2}{4}{3} {1, 2}{4}{4}	{1, 2}{4, 5}{3, 4} {3, 4}{2, 3}{2}	…	{4, 5}{2, 3}{1, 2} {3}{2, 3}{1}

Table 4: Hesitant-fuzzy evaluation matrix.

Subject	C_1	C_2	C_3	…	C_{96}
Sample Features	EN OI OD OT AA AI	EN OI OD OT AA AI	EN OI OD OT AA AI	…	EN OI OD OT AA AI
1	3.5 1.5 3.5 1 1.5 2.5	2 3.5 2.5 1.5 1.5 1	3 3.5 3.5 2 2 4	…	2 3.5 1.5 1.5 2.5 1
2	3.5 1.5 1 3.5 2 1.5 3.5	2 3.5 2.5 1.5 1.5 2.5	4 3.5 2 3 1.5 1.5	…	4 3.5 2 3 1.5 1.5
3	1 1 1.5 1.5 1 1	1 1 1.5 1 1 1	2 1 2.5 1.5 1 1.5	…	1.5 2.5 2.5 1.5 1 1.5
4	3.5 2 3.5 4 1.5 2	2 2.5 3 1.5 1.5 2	4.5 3 3 3.5 1.5 2.5	…	4.5 2.5 4 3.5 2.5 3
5	3 3 3.5 2.5 3.5 3	2.5 2.5 3 4.5 3.5 3	3.5 3 3.5 3.5 3.5 4	…	2 2.5 2.5 1.5 2.5 2.5
6	1.5 2.5 3 3.5 1.5 2.5	1.5 3 3 2.5 2.5 3.5	4.5 3 2.5 4.5 4.5 4	…	4.5 2.5 4 3.5 2.5 3
7	3.5 3 2.5 4 3.5 4.5	3.5 3 3.5 4 4 4	2.5 3 4 3.5 3.5 3.5	…	4.5 4 5 5 5 5
8	2.5 2 2 2.5 2 1.5	2 1.5 1 1 1 1	4 2.5 3 3.5 3 2	…	4.5 3.5 4.5 2 2.5 2.5
⋮	⋮	⋮	⋮	⋱	⋮
23	1.5 3.5 3.5 2 2 3.5	2 4 3 1.5 4 4	1.5 4.5 3.5 3.5 2.5 2	…	4.5 2.5 1.5 3 2.5 1

Table 5: Reliability analysis.

Data set	Cronbach's Alpha	N of Items
Value	0.976	577

complexity degrees of every sample are obtained and listed in Table 9.

4.6. Dimension Reduction of Neural Network Data Set. This section introduces the use of the PCA algorithm described in Section 3.3 to perform data dimension reduction on the sample complexity matrix in Table 6 and the hesitant-fuzzy evaluation matrix in Table 4. The MLE algorithm is adopted as the dimension reduction strategy [50]. In this way, more than 90% of data information is retained, and the data comparison after dimension reduction is shown in Table 10.

It can be seen that after PCA, the fuzzy evaluation matrix was compressed from the original six dimensions to five dimensions. However, the sample feature matrix of the complexity dimension can be compressed to two dimensions by the PCA algorithm. It provides the basis for neural network training with a small number of samples.

Table 6: Complexity degree matrix of samples.

Sample	Feature					
	EN	OI	OD	OT	AA	AI
0	0.548771	0.584216	0.609168	0.609168	0.856238	0.631096
1	0.808601	0.690832	0.663894	0.736484	0.709263	0.65
2	0.309168	0.517013	0.525236	0.396786	0.659074	0.556238
3	0.085066	0.359074	0.46673	0.090832	0.59707	0.491399
4	0.774764	0.743762	0.808601	0.817013	0.884216	0.76673
5	0.659074	0.67949	0.668904	0.645558	0.83327	0.690832
6	0.422495	0.422495	0.563516	0.517013	0.791399	0.67949
7	0.563516	0.491399	0.517013	0.556238	0.659074	0.577505
8	0.374102	0.443762	0.409263	0.436484	0.668904	0.451229
9	0.640926	0.62051	0.636106	0.65	0.715784	0.67949
10	0.35	0.636106	0.59707	0.458885	0.743762	0.663894
11	0.65	0.548771	0.548771	0.685066	0.674102	0.659074
12	0.690832	0.736484	0.696786	0.584216	0.89707	0.76673
13	0.2	0.07949	0.085066	0.241115	0.309168	0.225236
14	0.609168	0.32051	0.35	0.584216	0.614934	0.436484
15	0.090832	0.129395	0.129395	0.143762	0.136484	0.109263
16	0.491399	0.62051	0.508601	0.659074	0.668904	0.696786
...	...	...	...	...	...	...
96	0.685066	0.396786	0.436483	0.679489	0.614933	0.570604

Table 7: Complexity entropy of all features.

Feature	*EN*	*OI*	*O D*	*OT*	*AA*	*AI*
Entropy	0.972781574	0.975170034	0.982771291	0.97592165	0.991663718	0.986672343

Table 8: Weights of complexity features.

Feature	*EN*	*OI*	*O D*	*OT*	*AA*	*AI*
Value	0.236642	0.215876	0.14979	0.209342	0.072477	0.115873

Table 9: Complexity degree of samples.

Sample	0	1	2	3	...	95
Complexity Degree	3.70047259	4.145274102	3.024196597	2.170415879	...	3.383364839

Table 10: Data comparison after dimensions reduction.

Complexity after PCA	Fuzzy evaluation after PCA					
−0.518189663	−0.143490398	−0.614935017	0.633710287	−0.19771885	1.271722184	0.398531806
−1.094645356	1.40387409	−0.318278935	0.058520731	−0.302739578	1.338663212	0.894113214
0.274974012	−1.610609189	−1.999036566	0.229851835	0.290905989	−0.783309149	−0.484946857
1.283635824	−2.645106506	−0.080670741	−0.698590835	0.0236130354	−1.563307116	0.790976881
−1.698758004	0.434116341	−0.226322347	0.893042526	0.82571295	−0.078573414	0.250567461
−0.95385099	−0.172855553	0.118505627	−0.476348782	0.097839099	−2.515771325	0.132640173
0.077341782	−0.729233594	0.985001623	0.941788653	0.733555137	−1.681957829	−0.577861592
−0.295554003	0.243283864	−0.882831548	−0.489674961	0.243473972	1.344637579	0.256531062
0.457412258	0.132047054	−0.333163115	−0.49255516	−1.929329737	0.976861669	0.061394976
...	...	...	...	...	...	...
−0.215180898	2.107231765	−0.237435125	0.287610777	−2.113607129	−1.986364692	−1.446246687

4.7. Product Aesthetics Prediction Model Construction. This section constructed an aesthetic prediction neural network learning model, as shown in Figure 5(b). The number of input nodes is N, which indicates the effective feature number of input samples. Meanwhile, the number of hidden layers is two, and the number of output layer nodes is

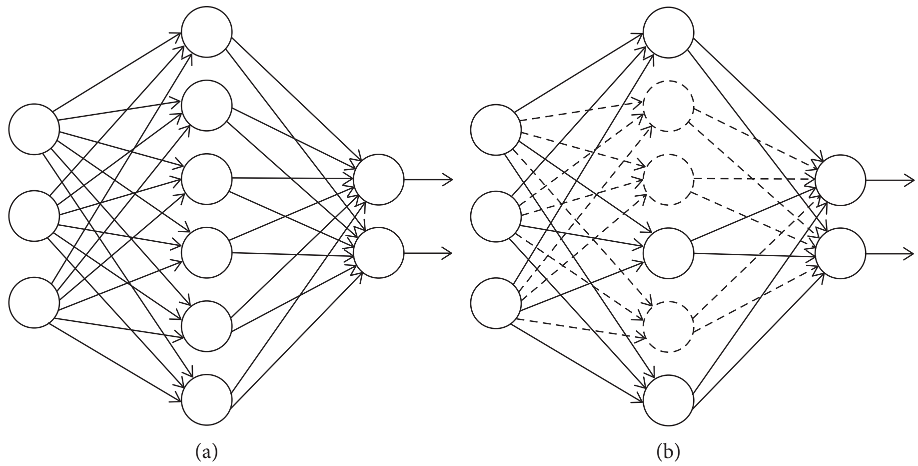


Figure 7: Structures of ANN with/without dropout. (a) ANN without dropout. (b) ANN without dropout.

five, meaning different subjective aesthetic evaluation values. The aesthetic evaluation is regarded as the label of training data, which is achieved according to the method discussed in Section 3.5.

It is considered that the increase in the number of nodes in the output layer will lead to a high error of the neural network trained by a small number of samples. In this case, the aesthetic score of this questionnaire adopted the fifth-order Likert scale without hesitation, so its score can be directly used as the label of model training without antihesitation.

The over-fitting problem in the training process will decrease the prediction accuracy of the trained model on the test data. The dropout technique was exploited to avoid over-fitting, and its principle is described as follows.

Figure 7(a) displays an ANN without regularization, which is susceptible to over-fitting. In the figure, the solid arrows linking the front and rear nodes imply no loss when the date is delivered from the upper layer to the lower layer. The ANN illustrated in Figure 7(b) consists of several dashed nodes. These indicate that some nodes are stochastically inactive in back-propagation and forward propagation. These nodes do not participate in the training of ANN. There are several advantages.

(1) The training effect is smoothed. The random deviation generated in the training process of ANN can be utilized to equalize the training parameters, which leads to a more accurate ANN model.

(2) Neuronal coupling is reduced. Since dropout makes a neuronal not always active in the recursive training of an ANN, the updating of weights no longer depends on the interaction of hidden nodes with fixed relationships. In this case, the situations where some features are compelling only if other certain features are activated are decreased.

(3) Like the basic idea of genetic algorithm, the species tend to adapt to the environment to survive. Environmental mutations can make it difficult for the species to respond in time. The emergence of gender can reproduce varieties that adapt to the new environment, thus effectively preventing over-fitting and avoiding species extinction when the environment changes.

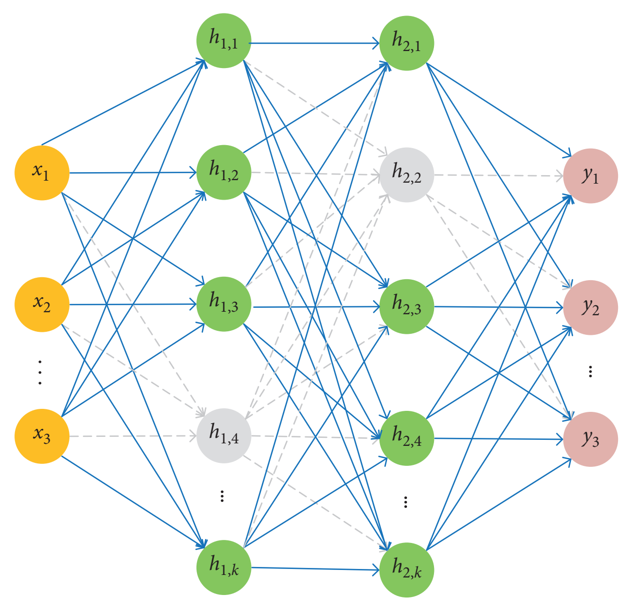


Figure 8: Dropout ANN used in the article.

Therefore, the dropout layer with a failure probability of 20% was adopted in this study. During each propagation, 20% of the nodes in the hidden layer will fail. It cannot update parameters to the back layer until the subsequent propagation begins. The final neural network structure is shown in Figure 8.

Here, $h_{1,4}$ and $h_{2,2}$ denote the nodes dropped in propagation. Dashed lines denote the connections between the nodes, and their weights are set to 0 to disable the updating of ANN parameters in this propagating process.

The number of nodes in the input layers varies according to different training methods. In this study, the dimensions of input data are two and five, as Table 10 shows. According to the principles listed in [51], the number of nodes in hidden layers should satisfy the requirement as given below:

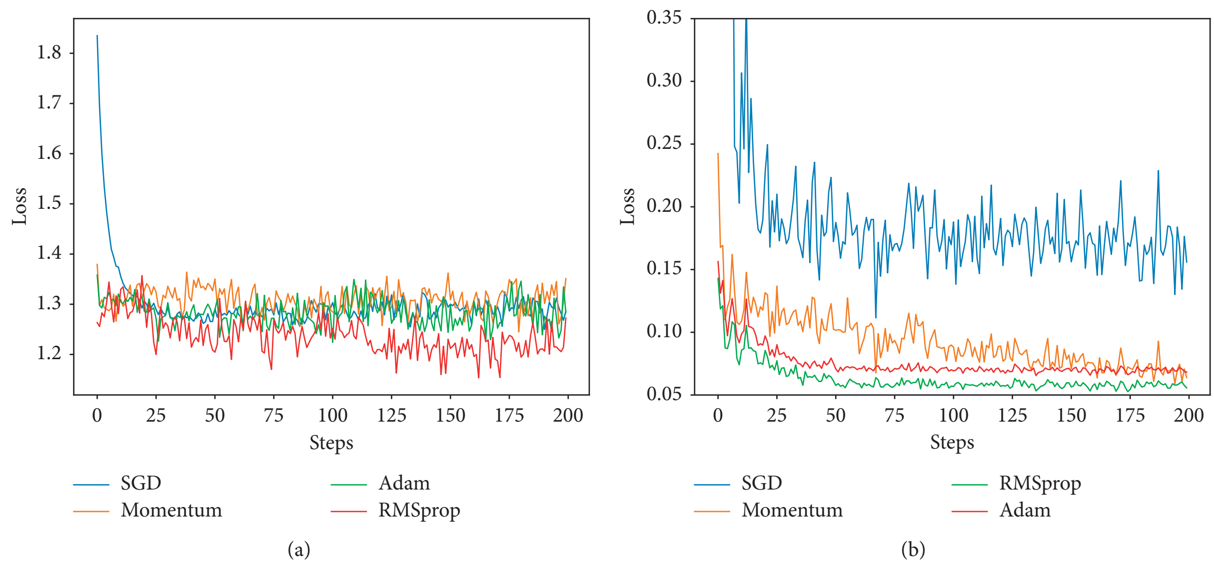


Figure 9: Performance comparison of the two models. (a) Loss of training with original data after PCA. (b) Loss of training with complexity degree after PCA.

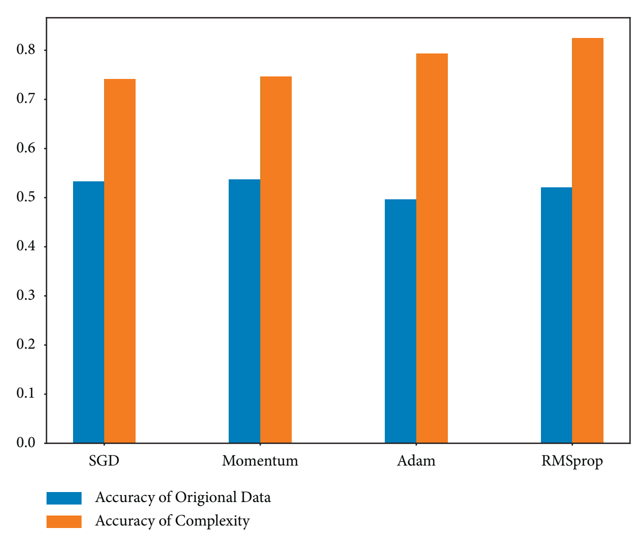


Figure 10: Accuracy achieved for different optimizers.

$$N_h \geq (N_{\text{in}} + N_{\text{out}}) * \frac{2}{3}. \tag{26}$$

Therefore, N_h was constrained to ensure the stability of the neural network structure during training process.

$$N_{\text{in}} = \max(N_i), N_i \in \text{set}(N), \tag{27}$$

where N denotes all the possible dimensions of the data input. In this study, N_{in} is 8. It is enough for training the ANN because a too large or too small value will lead to bad performance. According to the scoring categories, it is obvious that the number of nodes of the output layer should be set to 5.

To evaluate the effectiveness of the dimension compression method proposed, we took several different optimizers for comparison, including stochastic gradient descent (SGD) optimizer, random gradient descent optimizer with momentum (MSGD), and Adam optimizer and RMSProp optimizer, in this article. For brevity, the principles of these optimizers are not introduced here. The training process consists of 200 epochs. Meanwhile, the selected data samples are shuffled and divided into the training set and test set at a ratio of 7 : 3. Six sets of data are read for batch training in each epoch. Eventually, the trained model is evaluated on the test sets to analyze its accuracy. The convergence characteristics of the loss function and the mean-square error (MSE) and the model prediction accuracy are provided in Figure 9.

It can be seen from Figure 9 that the ANN tends to converge after 50 epochs, and the loss function did not decline due to the small number of samples. However, a great improvement in performance has been obtained.

Figure 11: Samples list in order of complexity.

In Figure 10, the blue and orange histograms, respectively, represent the accuracy of ANN trained on the original data and the complexity with dimension reduction by PCA. The result indicates that the proposed method can effectively compress the data dimension and significantly improve the prediction accuracy of the ANN. The samples sorted by complexity from low to high are shown in Figure 11. As can be seen, the results conform to people's subjective aesthetics to a certain degree.

5. Conclusion

Design activities tend to express designers' emotions, and design management pursues rational benefits. Correct design decisions can directly improve product design's success rate and increase enterprise benefits in design management. Therefore, the design decision is critical in design management. In this process, technical design decisions depend on the construction of mathematical and morphological models. The mathematical model of design decision-making usually studies the relationship between various factors in the decision-making object. It establishes a consumer aesthetic factor model and assists in evaluating the design scheme and the smooth implementation of product development in design management. This study uses a mathematical model to measure the complexity of users' visual cognition and establish the objective analysis and prediction of product aesthetic factors, which can guide product strategic decision-making and provide design innovation ideas for enterprise design management. The proposed method can help the design management evaluate the aesthetic feeling of the decision-making object through a quantitative questionnaire survey (the questionnaire is shown in the Figure 6).

Thus, it grasps the product's strategic decision in advance. Aiming at the problem that perceptual data are small and challenging to collect, we propose a machine learning model for small sample prediction, combined with perceptual engineering theory. The results show that the proposed model in this article can effectively improve the prediction accuracy and help designers quickly and conveniently obtain the design factors that affect the aesthetic feeling of decision-making objects in design management and the time and workforce consumption caused by surveys and interviews can be reduced. Effective design decision-making is the key to improving design management. Our method can help designers develop products with high user satisfaction to the greatest extent and help enterprises achieve the goal of gaining more substantial competitiveness.

The approach proposed in this article can be used for the intelligent aided design of product aesthetic evaluation by measuring product visual cognitive complexity. However, there left a few limitations. On the one hand, this article mainly focuses on complexity quantification and aesthetic prediction methods. Thus the shape of the product is not taken into consideration. Although it provides design decision-making thinking for design management, there is no more profound and systematic discussion of specific measures at the management level. Therefore, we will conduct a more comprehensive study on criteria based on this study in future research. On the other hand, this article adopts the control variable method to study the shape and visual cognition, eliminating variables such as color, material, and touch. However, it should be noted that these variables also impact the beauty of products. Therefore, these variables need to be further studied in the following work and the impact on different cultures and regions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

This work was supported by Shanghai Philosophy and Social Fund Project (Grant no. 2019EWY010).

References

[1] S. Lakhal, A. Darmon, J. P. Bouchaud, and M. Benzaquen, "Beauty and structural complexity," 2019, https://arxiv.org/abs/1910.06088.

[2] R. C. Wilson, A. Shenhav, M. Straccia, and J. D. Cohen, "The eighty five percent rule for optimal learning," *Nature Communications*, vol. 10, no. 1, p. 4646, 2019.

[3] H. Leder and M. Nadal, "Ten years of a model of aesthetic appreciation and aesthetic judgments: the aesthetic episode – developments and challenges in empirical aesthetics," *British Journal of Psychology*, vol. 105, no. 4, 2014.

[4] C. M. Hagerhall, T. Purcell, and R. Taylor, "Fractal dimension of landscape silhouette outlines as a predictor of landscape preference," *Journal of Environmental Psychology*, vol. 24, no. 2, pp. 247–255, 2004.

[5] S. U. Jian-Ning, L. I. Ming, A. M. Zhou, and S. T. Zhang, "Aesthetic measure evaluation model of product morphology and its application," *Journal of Lanzhou University of Technology*, 2018.

[6] P. Zhang and Y. Luo, "Study on complex systems from the perspective of design centric complexity," *Journal of Machine Design*, 2020.

[7] J. Delin, S. Sharoff, S. Lillford, and C. Barnes, "Linguistic support for concept selection decisions," *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, vol. 21, no. 02, pp. 123–135, 2007.

[8] N. P. Suh, "Complexity in engineering," *CIRP Annals*, vol. 54, no. 2, pp. 46–63, 2005.

[9] N. P. Suh, *Complexity: Theory and Applications*, Oxford University Press, Oxford, UK, 2005.

[10] S. Lloyd, "Measures of complexity: a nonexhaustive list," *IEEE Control Systems Magazine*, vol. 21, no. 4, 2001.

[11] A. Newell and J. C Shaw, *Human Problem Solving*, 1972.

[12] D. C. Donderi, "Visual complexity: a review," *Psychological Bulletin*, vol. 132, no. 1, pp. 73–97, 2006.

[13] J. Rigau, M. Feixas, and M. Sbert, "An information-theoretic framework for image complexity," in *Proceedings of the Computational Aesthetics 2005: Eurographics Workshop on Computational Aesthetics in Graphics, Visualization and Imaging 2005*, Girona, Spain, May 2005.

[14] A. Oliva, M. L. Mack, and M. Shrestha, "Identifying the perceptual dimensions of visual complexity of scenes," *Proc*

Annual Meeting of the Cognitive Science Society, vol. 3, no. 49, pp. 1041–1046, 2004.

[15] D. E. Berlyne and T. F. Maher, "Verbal and exploratory responses to visual patterns varying in uncertainty and in redundancy," *Studies in the new experimental aesthetics: Steps Toward an Objective Psychology of Aesthetic Appreciation*, vol. 10, no. 1, 1974.

[16] M. Baxter, *Product Design: A Practical Guide to Systematic Methods of New Product Development*, 1995.

[17] X. Gao, L. Wen, D. Tao, and X. Li, "Image quality assessment and human visual system," *Proc of the Visua*, vol. 7744, no. 5, pp. 17–19, 2010.

[18] R. Pieters, M. Wedel, and R. Batra, "The stopping power of advertising: measures and effects of visual complexity," *Journal of Marketing*, vol. 74, no. 5, 2010.

[19] L. Sun, T. Yamasaki, and K. Aizawa, "Relationship between visual complexity and aesthetics: application to beauty prediction of photos," in *Proceedings of the Workshop at the European Conference on Computer Vision*, Zurich, Switzerland, September 2014.

[20] L. A. Zadeh, "Fuzzy algorithms," *Information and Control*, vol. 12, no. 2, pp. 94–102, 1968.

[21] H. C. Wu, "Linear regression analysis for fuzzy input and output data using the extension principle," *Computers & Mathematics with Applications*, vol. 45, no. 12, pp. 1849–1859, 2003.

[22] L. H. Chen, W. C. Ko, and F. T. Yeh, "Approach based on fuzzy goal programing and quality function deployment for new product planning," *European Journal of Operational Research*, vol. 259, no. 2, 2017.

[23] H. Liu, "An integrated fuzzy decision approach for product design and evaluation," *Journal of Intelligent and Fuzzy Systems: Applications in Engineering and Technology*, vol. 25, no. 3, 2013.

[24] J. Hirokawa, A. Vaughan, P. Masset, T. Ott, and A. Kepecs, "Frontal cortex neuron types categorically encode single decision variables," *Nature*, vol. 576, pp. 446–451, 2019.

[25] O. Kulak and C. Kahraman, "Fuzzy multi-attribute selection among transportation companies using axiomatic design and analytic hierarchy process - sciencedirect," *Information Sciences*, vol. 170, no. 2–4, pp. 191–210, 2005.

[26] H. C. Shen and K. C. Wang, "Affective product form design using fuzzy kansei engineering and creativity," *Journal of Ambient Intelligence and Humanized Computing*, vol. 7, no. 6, pp. 875–888, 2016.

[27] S. Chanyachatchawan, H. B. Yan, S. Sriboonchitta, and H. Van Nam, "A linguistic representation based approach to modelling kansei data and its application to consumer-oriented evaluation of traditional products," *Knowledge-Based Systems*, 2017.

[28] Y. Yang, "Kansei evaluation method of product form design based on hesitant fuzzy linguistic term sets and particle swarm optimization," *Journal of graphics*, 2021.

[29] L. Wang and C. Zhao, "The expert synthesis and integration research method based on hesitant fuzzy language," *Systems Engineering-Theory & Practice*, 2021.

[30] H. Liao, Z. Xu, and X.-J. Zeng, "Hesitant fuzzy linguistic vikor method and its application in qualitative multiple criteria decision making," *IEEE Transactions on Fuzzy Systems*, vol. 23, no. 5, pp. 1343–1355, 2015.

[31] I. Beg and T. Rashid, "Topsis for hesitant fuzzy linguistic term sets," *International Journal of Intelligent Systems*, vol. 28, no. 12, 2013.

[32] R. M. Rodriguez, L. Martinez, and F. Herrera, "Hesitant fuzzy linguistic term sets for decision making," *IEEE Transactions on Fuzzy Systems*, vol. 20, no. 1, pp. 109–119, 2012.

[33] F. P. Ava, "A large-scale database for aesthetic visual analysis," in *Proceedings of the IEEE Conference on Computer Vision & Pattern Recognition*, Providence, RI, USA, June 2012.

[34] Y. Kao, K. Huang, and S. Maybank, "Hierarchical aesthetic quality assessment using deep convolutional neural networks," *Signal Processing: Image Communication*, vol. 47, pp. 500–510, 2016.

[35] Y.-C. Lin, C.-H. Yeh, and C.-C. Wei, "How will the use of graphics affect visual aesthetics? a user-centered approach for web page design," *International Journal of Human-Computer Studies*, vol. 71, no. 3, pp. 217–227, 2013.

[36] B. K. Behera and R. Mishra, "Artificial neural network-based prediction of aesthetic and functional properties of worsted suiting fabrics," *International Journal of Clothing Science & Technology*, vol. 19, no. 5, 2007.

[37] M. Xu, F. Chen, L. Lu et al., "Bio-inspired deep attribute learning towards facial aesthetic prediction," *IEEE Transactions on Affective Computing*, vol. 12, no. 1, 2018.

[38] A. Zhou, S. U. Jianning, S. Yan, J. Ouyang, and S. Zhang, "Product multi-image prediction model based on aesthetic measure of form," *Journal of Graphics*.

[39] L. K. Wong and K. L. Low, "Saliency-enhanced image aesthetics class prediction," in *Proceedings of the IEEE International Conference on Image Processing*, Cairo, November 2009.

[40] W. N. Wang, L. Wang, M. Q. Zhao, C. J. Cai, and X. M. Xu, "Image aesthetic classification using parallel deep convolutional neural networks," *Acta Automatica Sinica*, 2016.

[41] J. Zhang, J. Yu, K. Zhang, X. S. Zheng, and J. Zhang, "Computational aesthetic evaluation of logos," *ACM Transactions on Applied Perception*, vol. 14, no. 3, 2017.

[42] V. Torra, "Hesitant fuzzy sets," *International Journal of Intelligent Systems*, vol. 25, no. 6, pp. 529–539, 2010.

[43] Y. Dai, Z. Xu, L. Yan, and Q. Da, "New evaluation scale of linguistic information and its application," *Chinese Journal of Management Science*, 2008.

[44] G. L. Geissler, G. M. Zinkhan, and R. T. Watson, "The influence of home page complexity on consumer attention, attitudes, and purchase intent," *Journal of Advertising*, vol. 35, no. 2, 2013.

[45] M. L. Simmel and R. Arnheim, "Art and visual perception: a psychology of the creative eye," *American Journal of Psychology*, vol. 68, no. 2, 1955.

[46] F. Attneave and Fred, "Some informational aspects of visual perception," *Psychological Review*, vol. 61, no. 3, pp. 183–193, 1954.

[47] M. Turk and A. Pentland, "Eigenfaces for recognition," *Journal of Cognitive Neuroscience*, vol. 3, 1991.

[48] X. Wu, M. Yang, and Z. Su, "Pleasurable emotions of product design," in *Proceedings of the IHSI 2021 Conference*, Palermo, Italy, February 2021.

[49] E. R. Babbie, "The practice of social research," *Contemporary Sociology*, vol. 5, no. 2, 1976.

[50] T. P. Minka, "Automatic choice of dimensionality for pca," ", https://tminka.github.io/papers/pca/, 2001.

[51] S. W. Hsiao and H. C. Huang, "A neural network based approach for product form design," *Design Studies*, vol. 23, no. 1, pp. 67–84, 2002.

Hindawi
Complexity
Volume 2022, Article ID 7734580, 14 pages
https://doi.org/10.1155/2022/7734580

Research Article

Utilizing Blockchain Technology to Manage the Dark and Bright Sides of Supply Network Complexity to Enhance Supply Chain Sustainability

Weili Yin and Wenxue Ran

School of Logistics, Yunnan University of Finance and Economics, Kunming 650221, China

Correspondence should be addressed to Wenxue Ran; ranwxa@vip.sina.com

Received 23 January 2022; Accepted 17 May 2022; Published 17 June 2022

Academic Editor: Ning (Chris) Chen

The supply network becomes more fragile as it becomes more complex, affecting the core firm's performance. While previous research on supply network complexity existence paradox. Therefore, to study the nature of supply network complexity, this paper divides the supply chain complexity utility into positive and negative valences based on the valence framework and divides supply chain complexity into supply base complexity, customer base complexity, and logistics base complexity. Based on the trustworthiness and transparency characteristics of blockchain technology, this paper investigates how to use blockchain technology to reduce the negative valence of supply chain complexity while adapting to or improving the positive valence to improve enterprise competitiveness and supply chain sustainability. As a result, the focus of this paper is on how to better manage supply chain complexity using blockchain technologies to increase supply chain sustainability and viability.

1. Introduction

Due to the outbreak of COVID-19, supply chains around the world have been disrupted to varying degrees [1, 2]. Therefore, in order to improve supply chain resilience and their ability to cope with risks, more and more studies have focused on the supply network complexity to improve the supply chain resilience [3]. Supply chain complexity management is becoming increasingly important. For the management of a complex supply chain, achieving supply chain transparency is crucial, and as supply chains become more complex, achieving supply chain transparency becomes increasingly difficult.

The network of firms is getting increasingly complex and technology-oriented, according to organizational theory, and the network of enterprises is more sensitive to accidents [4]. Perrow [5] explains why complex social technology systems fail with normal accident theory, linking the occurrence of accidents to the structure and technology of the underlying system. According to normal accidents theory, complexity is one of the key factors for a high accident rate in the social technology system. The occurrence of destructive events in a system is influenced by complexity in two ways, the first of which is related to the occurrence of destructive events in complex systems: a system with a large number of elements is likely to be more harmful than one with fewer elements [6]. The second mechanism has to do with management capacity, or the ability to recognize and prevent damaging events before or after they happen. The occurrence of catastrophic events in the supply chain can be influenced by supply chain complexity as a complex system. As a result, improving supply chain transparency is one of the most essential components in addressing the negative effects of supply chain complexity.

The supply chain firm offers a lot of potential for blockchain technology as a disruptive technology. The most significant advantage of blockchain technology in the supply chain is that it improves information exchange and transparency amongst supply networks. Blockchain technology can be utilized to accomplish whole-process monitoring and information traceability in the medical and fresh food industries [7]. Similarly, as global supply networks become increasingly complex [8, 9], information asymmetry and uncertain risks in supply chains increase, which makes it more likely to lead to bullwhip effects and ripple effects that exacerbate the negative impact of the supply chain risks. With the increase in the number of participants in the supply network, the lack of understanding and trust between different actors is further caused [10]. Blockchain technology can assure the reliability and transparency of information transmission on the supply network and increase confidence between transaction subjects due to its inherent technical properties [11]. Therefore, blockchain technology has very high applicability in the field of supply chains [12].

In the past, many studies linked higher supply network complexity to poor firm performance, but recent research has revealed that complexity is an important factor in supply network organizations' access to survival and development space, which has a significant impact on changes in the external environment, changes within organizations, and continuous performance optimization. The ability of a network organization to manage its complexity and quickly adapt to the complexity of the external environment is critical to its existence. The purpose of this study is to use blockchain technology to manage supply chain complexity, as well as to identify the meaning and dimension of supply chain complexity, and to analyze the relationship between blockchain technology and supply chain complexity.

(1) The dimension of supply chain complexity is proposed in conjunction with the relevant study situation

(2) Previous research has found that supply network complexity has a detrimental impact; however, this study investigates the dual impact of supply network complexity

(3) What is the relationship between blockchain technology and the supply network complexity

(4) How can blockchain technology be used to respond to and adapt to the supply chain's complexity

This paper contributes to the theory in the following aspect: first, this study is based on the valence theory and put out that supply chain complexity can be divided into positive valence and negative valence and put forward that we can utilize blockchain technology to manage supply chain complexity. Second, this study put forward three propositions that utilizing blockchain technology can help manage the supply chain complexity to enhance supply chain sustainability. Third, this paper put forward that ambidexterity management of the supply network complexity by using blockchain technology, blockchain technology can be used to respond to the positive and negative valence of supply network complexity from the perspective of ambidexterity.

2. Theoretical Background

2.1. Research on Blockchain Technology in the Field of Supply Chains. By use of blockchain technology in the supply chain has raised interest recently, although the practical value of blockchain technology in dealing with supply network complexity has yet to be investigated. Blockchain, as a leading technology, is transforming and redefining the interactions between actors in logistics and supply chain networks. Some research indicates that the implementation of blockchain technology in the supply chain mitigated the negative impact of COVID-19 on companies under the impact of COVID-19 [13]. The most essential feature of blockchain technology is that it may boost the transparency of information transfer over the supply network while maintaining security [14]. The adoption of blockchain technology in the field of the supply chain can also improve the adaptability of the supply chain and thus improve enterprise performance [15]. As supply networks become more complex, supply chain pain points such as asymmetric information and supply chain risk rise. Because of the absence of trust and real-time data transmission between many stakeholders, a supply chain information system based on existing blockchain technology can improve supply chain resilience and risk level. [16]. As a technology applied in the field of the supply chain, blockchain focuses on connectivity. In the process of technology implementation, attention should be paid to factors affecting connectivity, interactions, and elasticity in the supply chain [17]. For the adoption of blockchain research, the research shows that the Unified Theory of Acceptance and Use of Technology (UTAUT) model, the Task-Technology FIT (TTF), and the Information System Success (ISS) Mode are key factors influencing the adoption of blockchain technology by supply chain employees [18]. However, there are some inhibitors to the adoption of blockchain technology in supply networks. For example, Blockchain technology is a high-cost storage medium, and its adoption is only justified when the benefits of deploying blockchain technology surpass the expenses [19]. The adoption of blockchain technology is also an excellent choice for long-term development, as it has the potential to drastically alter firm development models due to its immutability, security, credibility, and transparency. Blockchain technology will not only have a significant impact on the logistics industry, but it will also have a significant impact on business models [20]. Supply chain collaboration is another area where blockchain technology has a lot of potential. Blockchain technology has the potential to affect not just supply chain collaboration and increase trust in B2B partnerships, but also to strengthen cooperation and address vulnerability issues connected to potential risks and the negative impact of technical legacy problems [21].

Following a review of the relevant literature on blockchain technology and its use in the supply chain, it was discovered that blockchain technology has a lot of potential in the supply chain, and the technological characteristics of blockchain, such as traceability, tamper-proofing, and asymmetric encryption, may indeed provide the safe and reliable transmission of information in the supply chain to achieve the reliable. From the perspective of the increasingly complex supply network, the supply network's reliability and transparency are the initial requirements for managing a complex supply chain. This technical characteristic of blockchain allows firms to leverage the technology to better manage the supply chain's complexity.

2.2. Supply Network Complexity. A wider choice of products, shorter product life cycles, and lower production costs are pushing enterprises to their limits, resulting in supply chain management complexity. To manage this complexity, management must understand the key complexity drivers and their inter-relationships. To manage this complexity, management must understand the key complexity drivers and their inter-relationships. The complexity of a supply network can be separated into two categories: structure and behavior complexity [6]. The former is known as structure complexity, while the latter is known as dynamic complexity (or operational complexity), and this definition has been the foundation for future studies on complexity.

Previously, the impact of supply chain network architecture on the core enterprise relationship management strategy was assessed. [22], they examined five factors that make up the supply network structure and the impact on four relationship management strategies [22]. There are also studies focusing on structural attributes of the supply chain: formalization and centralization, and the relationship between structural attributes and operational performance [23]. There is also a way to match the product structure with the supply chain structure [24]. While many studies have shown that rising supply chain complexity is linked to worse firm performance in the past, a recent study reveals that increasing supply chain complexity harms firm performance while benefiting innovation and financial performance [3]. Numerous empirical research on supply networks have shown that product diversification, multimarket, and multichannel strategies can increase a company's market performance [25]. In places with high supply chain complexity, formal and societal restraints have both negative and positive effects on operational performance, especially as supply networks become more complex [26].

The normal incident hypothesis can be used to explain how adverse event traceability happens in various supply networks since irregularities are more common in complex supply networks. The normal incident hypothesis can be used to explain how adverse event traceability happens in various supply networks since irregularities are more common in complex supply networks. [27]. Studies have identified three characteristics of supply base complexity: the number of suppliers, supplier differences, and supplier interrelationships [28, 29]. Some studies divide the supply structure complexity scale into visible and less apparent levels since many supply chain structure studies focus on network-level characteristics and overlook supply-base characteristics. Some aspects of supply network complexity amplify the impact of disruptions, while others improve resilience following disruptions [30]. Some scholars have suggested supply chain complexity can be divided into three categories: upstream, internal manufacturing, and downstream complexity [31].

To resolve the paradox of the preceding study, this study uses the valence framework to classify the supply network's complexity into positive and negative valences. The theory of value is used to explain consumer behavior and comes from the domains of economics and psychology. The valence framework proposed by Peter and Tarpey [32] takes into account both positive and negative factors on individual decision-making behavior. The core premise of the valence framework is that individuals make decisions to minimize the negative impact and maximize the positive impact [33]. As a result, we employ the valence framework to investigate the positive and negative consequences of supply network complexity. Therefore, the impact of supply network complexity is classified into positive and negative valences based on the value framework, which is utilized to explain the beneficial and harmful consequences of previous supply chain complexity research (which answer the second question). Investigating how blockchain technology can be utilized to address supply network complexity to increase the supply network's ability to adapt to risks and improve supply chain viability.

2.3. Blockchain Technology, Supply Chain Complexity, and Supply Chain Disruption. The supply chain is the process of getting the correct products to the right place at the right time, and coordination, planning, and control are the most important aspects of this process [34]. Coordination requires the establishment of systems to increase transparency throughout the supply chain. Increased supply network transparency can also help firms react quickly to shifting customer and social awareness [34]. In supply chain management, enterprises face common challenges from upstream and downstream, where they need to manage consumer and market preferences, and upstream, where they need transparency to manage their complex supply networks. Firms may not be able to determine where their Tier 1 suppliers buy or send materials, and assessing the quality of supplier products and the openness of the production and supply processes becomes more challenging if Tier 1 suppliers have many manufacturing locations around the world.

Global and local supply chains differ in terms of supply chain complexity, adaptability, and complexity. Global supply networks are more complex and flexible since they have a wider supply base to choose from. Local supply chains, on the other hand, are less complex and thus more adaptable to market changes, especially when influenced by extreme events. Supply network risks are exposed as supply chains grow in size and complexity, and effective supply chain transparency is the most important factor in controlling supply chain complexity. The continual advancement and development of modern information technology provide a good opportunity to manage the supply chain's complexity. Effective transparency policies and processes are required not simply to keep or restore supply chain partners' trust.

In terms of the relationship between blockchain technology and the supply chain, firms that use new blockchain technologies to better understand partner operations and reduce supply chain risk benefit from transparency technologies [35, 36]. Blockchain technology can be seen as an opportunity to leverage existing supply chain resources and competitiveness, its traceability, which can be viewed as an exploration technology or a relationship-building technology, is the essential invention of blockchain technology [37]. The most significant feature of blockchain technology is traceability, which improves supply chain transparency, strengthens supply chain management, facilitates information sharing among partners, and lowers the cost of supply chain coordination, thereby improving the supply chain's ability to respond to disruption risk. As a result, integrating blockchain technology into the supply chain has a positive impact on the supply chain's viability and the competitiveness of firms [38].

3. Dimensions of Supply Network Complexity

According to previous research, supply chain complexity can have a dual effect on resilience after a supply chain interruption; on the one hand, supply chain complexity can help with recovery ability after a supply chain interruption; for example, higher supply base complexity allows firms to use more supplier after an interruption, which improves their ability to recover. On the other hand, supply chain complexity can be detrimental to recovery ability after a supply chain interruption; for example, higher supply base complexity can enable enterprises to use more suppliers after the interruption, improving their ability to recover [30]. Therefore, according to the location of the supply network, this study divides the complexity of the supply network into supply-based complexity, customer-based complexity, and logistics complexity (which response to the first question) (Figure 1).

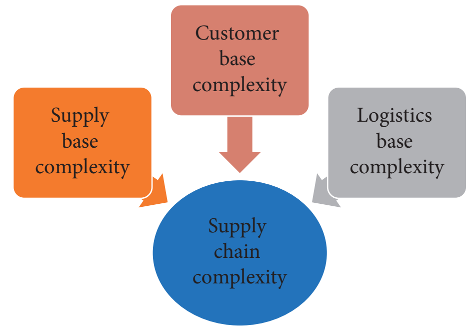


Figure 1: The dimensions of supply network complexity.

3.1. Supply Base Complexity. Increased visibility of information improves product traceability and authenticity, providing a basis for industries that need to track their products [39]. In addition, by adopting smart contracts, agreements can be automated in-network transactions [40], aiming at simplifying the supply chain process, thus improving the efficiency of the supply chain. Information sharing through blockchain technology reduces the physical movement and duplication of information and latency of files, improving inventory management and waste in the supply chain for more accurate demand forecasting [41]. The spread of digital technology has contributed to the interdependence and management activities between businesses and supply networks in the industry. Treiblmaier [41, 42] believes that blockchain solutions can change the concept of interorganization relationships by enhancing the exchange of trusted information between companies.

The complexity of the supply base increases when the core company has many suppliers that vary in geography, enterprise size, organizational culture, and technical capabilities [43, 44]. At the same time, many of these suppliers have inconsistent lead times and extended lead times, which adds to the supply base's complexity. The increasing complexity of maintaining a supply base is often accompanied by an increase in transaction costs and the number of interactions and interfaces that must be managed [29, 45]. As the supply base increases, core companies often face higher information processing requirements, accompanied by increased communication costs [43]. From a supplier heterogeneity perspective, the geographic location of different suppliers and the differences between different industries increase the burden on core enterprises to respond to different suppliers [28, 43]. Thus, as transaction costs increase, the degree of control over the supply base decreases with complexity, making it more difficult for core firms to deal with supplier opportunism [45]. In terms of communication quality, as well as the scope and timeliness of information sharing [46], managing a wide range of suppliers can frequently result in difficult-to-control situations.

The increasing complexity of the supply chain may be advantageous to company innovation. Internal and external knowledge are the two main sources of knowledge for firms [47]. Open innovation shows that companies can innovate by seeking knowledge from the outside. Knowledge-based view shows that the more actors you reach in the network, the easier it is for companies to innovate [29]. Due to the massively increased complexity of the supply base, the core firm now has a significant number of suppliers from various industries and technical capabilities, allowing it to harness knowledge from other suppliers to drive innovation [44].

3.2. Customer Base Complexity. Supply chain organizations may address a variety of consumer expectations by employing blockchain technology, quickly recalling products from the market when disrupted, automate business processes with integrated responses to product quality by tracking product chains. Supply chain complexity refers to the extent to which an organization's supply chain consists of a large number of different elements that interact in unpredictable ways [48].

Customer base complexity usually refers to downstream complexity, which is frequently associated with customer numbers and product types. A broad customer base and a wide variety of finished goods with a shorter life cycle contribute to the complexity of the customer base when the core enterprise's aims meet changing consumer needs and expectations [49]. When the complexity of the customer base is high, customers with a large deviation of customer demand will hurt the operating efficiency of enterprises [31]. Transaction costs also increase with more and more diverse customers, reducing the efficiency of companies in managing their customer base. As customers become more geographically dispersed, it is common for core businesses to increase inventory costs and cash withdrawal cycles [50]. Furthermore, a diverse client base may compound the impact of fluctuations in demand in downstream supply chains, affecting the business's success.

3.3. Logistics Complexity. Since there are so many carriers in a supply network that represent network connectivity, there is a need for greater carrier monitoring and coordination [29]. Firms must better coordinate the multiparty entities in the supply chain to efficiently manage the complex supply network. Coordinating logistical activities among many carriers, is more challenging, as organizations must manage several partnerships among carriers, which are frequently interconnected [51]. More carriers may mean more unreliable delivery options for the core organization, as it is difficult for the core enterprise to control all carriers.

According to standard accident theory, increased logistical complexity increases the likelihood of supply chain disruption. When a high level of logistical complexity exists, managers have a better chance of discovering and diagnosing problems [52]. As a result, the number of carriers in the supply network increases, thereby increasing the complexity of logistics. Increased logistics complexity may provide a higher level of flexibility for the business after the outage [53]. When problems occur in one transportation link, enterprises can choose other carriers to ensure the continuity of transportation. When an enterprise has multiple carriers, it can quickly transfer products among carriers [54]. As a result, firms require more optional carriers to improve their ability to use logistics networks more flexibly and prevent order delays.

For firms with low logistical complexity, on-time and reliable delivery can be a problem. According to research, organizations that are not sufficiently diversified and rely too much on crucial suppliers recover more slowly from interruptions [55]. These actual cases reinforce the importance of diverse third-party logistics carriers. In the event of a disruption, the availability of alternatives allows shippers to transfer to carriers that perform better in the event of an outage at minimal conversion costs to carriers that perform better in the event [30]. In this setting, implementing a diverse portfolio of complex delivery systems can improve the firm's ability to respond to threats while also assisting the core firmly in avoiding potential risks.

4. The Relationship between Blockchain Technology and Supply Networks Complexity

One of the causes of supply chain complexity is that supply chain transparency reduces as the degree of the supply network grows. From the standpoint of transaction cost economics, it encompasses constrained rationality and opportunism. Furthermore, due to supply chain complexity creating a more uncertain environment, it is likely to enhance supplier opportunism and limit organizations' ability to detect supplier opportunism.

Xiao and Qi [56] emphasize that information sharing and good communication between multiple layers and channels are key strategies to avoid supply chain disruptions caused by fluctuations in demand. Product diversity is also an important manifestation of customer base diversity, the optimum design of a product may not be suitable for another product. Therefore, when product variety is high, more efficient supply chain coordination is required [57]. Another key factor that drives supply chain complexity is the product life cycle; a shorter product life cycle means faster supply chain design adjustments to satisfy different levels of demand uncertainty at various stages, as well as faster production and shorter lead times [58].

As seen in the following three images, we mainly employ OPEN KNOWLEDGE MAPS, a visual tool, to generate the three main themes of my research. This visualization tool generates keywords based on the metadata output of a huge amount of articles. To create keywords between articles, search terms are mostly derived from the title, abstract, author, journal, and topic keywords. Figure 2 is connected to blockchain research, Figure 3 is related to supply chain complexity, and Figure 4 is about the overlap of blockchain and supply network complexity. We can see from the key terms in these three figures that there are currently few papers that study both blockchain technology and supply chain complexity. Current research on blockchain technology and supply chain complexity are two relatively independent research streams. As a result, we assume our research into how to use blockchain technology to manage supply chain complexity has some merit.

4.1. Why Supply Chain Complexity Management Requires Visibility and Transparency. Visibility makes it easier for firms to respond to supply chain risk incidents, therefore having a high level of visibility is crucial. The danger of supply chain vulnerability grows as more stakeholders become involved in today's society, and risk management becomes increasingly important. As the supply base of the core firm becomes more complicated, the core firm will need more suppliers to strengthen its ability to respond to threats. However, as the complexity of the supply base grows, it becomes more difficult for the enterprise to control the behavior of members of the supply network, and the supply network's transparency and visibility decrease. As a result, improving supply network transparency and visibility is the most crucial thing to do to manage supply chain complexity as supply networks become increasingly complex.

Increased transparency in the supply network is not only to meet regulatory requirements but also to optimize operations, ensure product quality, and ensure the sustainability of processes [59]. Supply chain transparency solutions enable knowledge integration to improve decision quality, lowering perceived risk, and enhancing control over partner behavior, allowing for better management of supply chain complexity's negative effects. By increasing transparency

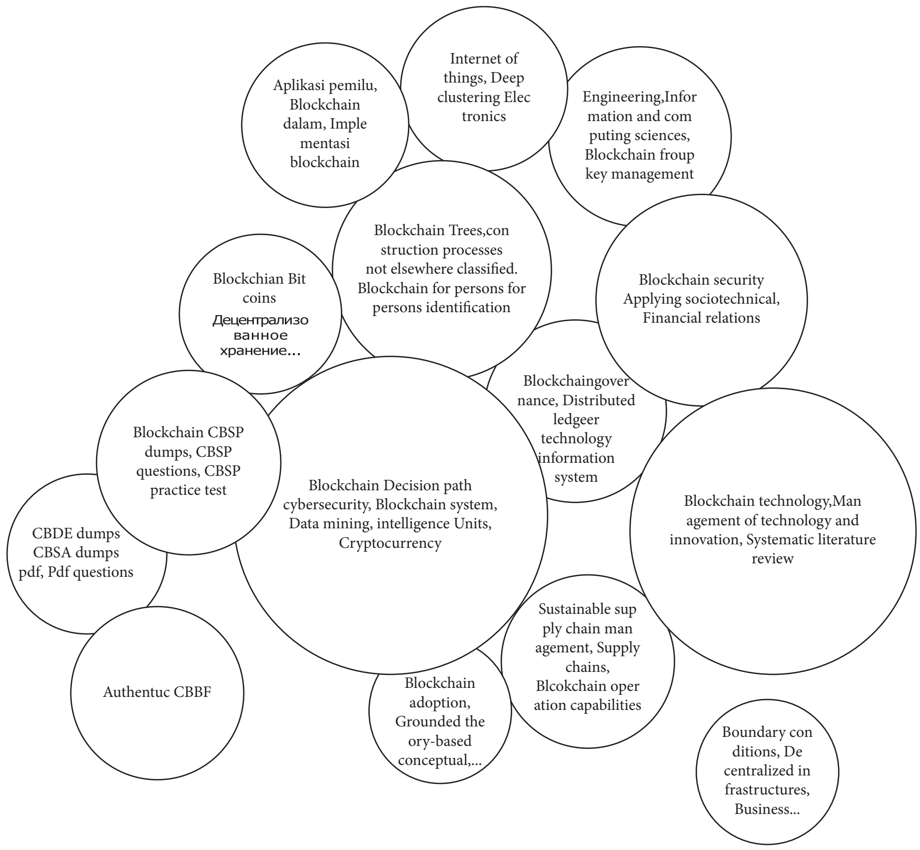


Figure 2: Overview of research on blockchain. Source: Open Knowledge Maps (2022). Overview of research on blockchain. Retrieved from https://openknowledgemaps.org/map/5f73499253c87dec9f0a22736f1bcf0b (2 Mar 2022).

between supply chain partners, the subjective perception among supply chain partners can be improved [60] and improve the trust between supply chain partners, reducing the uncertainty and inherent risk of supply chain partners' behavior [61, 62]. Supply chain transparency enables companies to establish response strategies for external and internal outages, thereby reducing operational risk [63]. Suppliers are less likely to take opportunistic or risky actions in a complex supply network as transparency rises, lowering costs and shortening production lead times. Increased accountability and control over the supply chain come from having visibility into the upstream supply base and the downstream consumer base. Furthermore, effective transparency techniques can reduce supply chain partner uncertainty as well as the supply chain's structural complexity.

4.2. Blockchain as a Governance Mechanism to Address Supply Chain Complexity. The more complex a supply chain is, the less visibility and transparency it has, and companies are dealing with a more dynamic environment, which is especially true in today's VUCA world. It is more uncertain, making it more difficult to manage a complex supply chain. The focus for core firms is on building better supply chain transparency strategies based on the existing supply chain structure, which can only change very little in a short period [64]. Complex supply chains have multiple supply chain levels, making it difficult to increase supply chain transparency alone for a single core enterprise [65], and for core enterprises, it is expensive, complex, time-consuming, and laborious to disclose ESG data of supply chain [65, 66] to control all levels of the supply chain.

4.2.1. The Relationship between Blockchain Technology and Supply Base Complexity. The number of suppliers affects the ability of core enterprises to manage suppliers and sub-suppliers, thereby negatively affecting the visibility and transparency of the supply chain [67]. Through interconnectedness between supply chains, the deployment of blockchain technology in the supply chain can promote supply chain transparency and facilitate information sharing and collaboration among supply chain members. The supply chain is composed of multiple actors which may have different or conflicting goals [68]. Therefore, to address the issues, a common governance structure for supply chain members to manage supply chain partners through particular norms and agreements must be implemented. Blockchain as an information system can establish norms and governance mechanisms in the supply chain [69]. Distributed ledger technology, which provides authenticity and traceability by storing data on blocks that are difficult to tamper with, was the initial definition of blockchain technology. Blockchain technology's intrinsic nature and potential to transform organizations, industries, and supply networks [70].

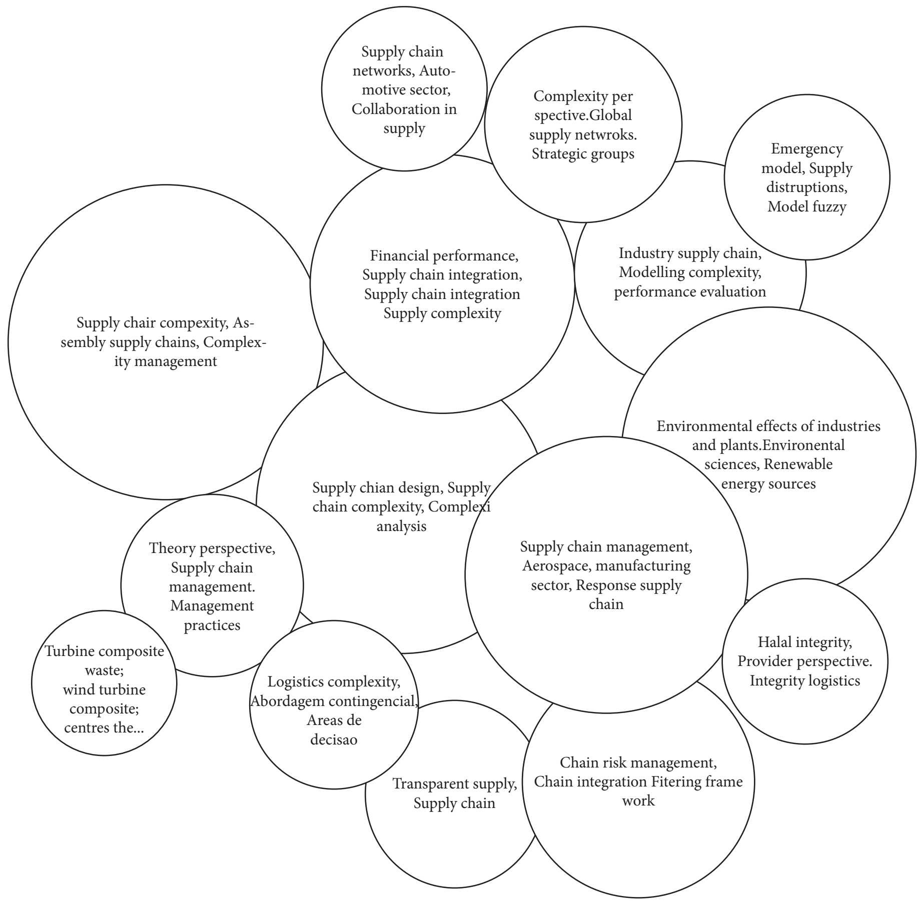


Figure 3: Overview of research on supply chain complexity. Source: Open Knowledge Maps (2022). Overview of research on supply chain complexity. Retrieved from https://openknowledgemaps.org/map/7ab5811ae0ec2eb91d0c795129953a82 (2 Mar 2022).

It gets more difficult to control and trace the flow of information in the supply chain as the supply network becomes more complicated [71, 72]. The blockchain serves as a platform to integrate and manage information from a variety of complex and multilevel participants and channels [73]. The information may be viewed in a safe environment by supply chain partners and entities, and the transparency and security of blockchain technology have a substantial impact on supply chain objectives. Blockchain technology can support supply chain management by executing smart contracts [74]. By executing smart contracts between supply chain partners, processes can be fully automated and information flows between processes can be accelerated [75]. The transparency and verifiability of blockchain information tend to reduce the need for trust between supply chain partners [76], and supply chain complexity can be better managed through coordination among supply chain partners.

Blockchain technology provides a system that connects multiple supply chains [76, 77]. Blockchain-supported governance structures make better use of the visualization of information for coordination among supply chain partners [78]. As a result, better cooperation and coordination among supply chain participants are required to better manage supply chain complexity. Blockchain technology provides a high level of transparency, which aids strategic decision-making. It may also be successfully used in modern supply networks to improve supply chain sustainability, where it is difficult to track complex data from several departments and activities across organizations [79]. Blockchain technology's information can change the supply chain's flow because of its trustworthiness, authenticity, immutability, and traceability. The use of blockchain technology can identify redundant operations or procedures in the supply chain, reducing the requirement for third parties.

Through the above analysis, we propose the following:

H1: utilizing blockchain technology can help manage the supply base complexity to enhance supply chain sustainability.

4.2.2. The Relationship between Blockchain Technology and Logistics Base Complexity. By combining GPS and tracking devices, blockchain-based solutions provide reliable information on product delivery, distribution networks, and logistics performance [80]. The existing supply network involves various third-party logistical activities, and blockchain technology can guarantee the validity and trustworthiness of the information. Blockchain is an integrated system that connects individual supply chain entities while allowing for quick verification of required supply chain information and tracking of essential transportation data

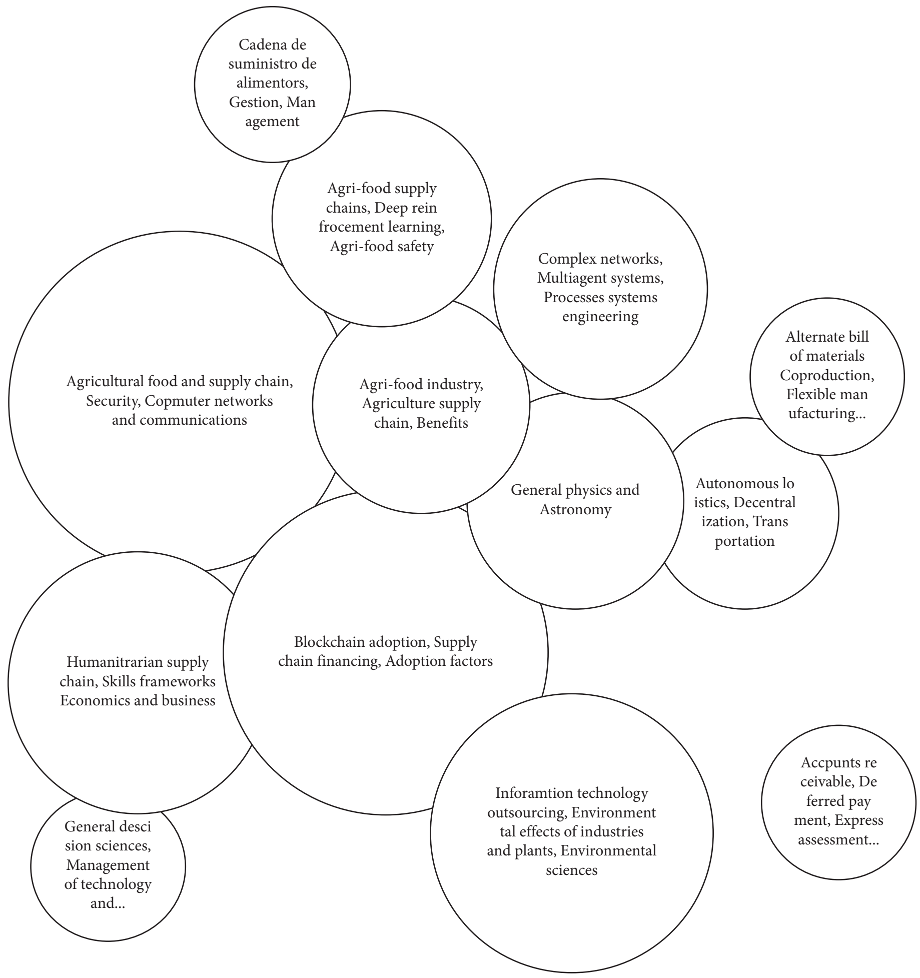


Figure 4: Overview of research on blockchain; supply chain complexity. Source: Open Knowledge Maps (2022). Overview of research on blockchain; supply chain complexity. Retrieved from https://openknowledgemaps.org/map/d8a0604af922b2eb1444eb6d5d153a75 (2 Mar 2022).

[81]. The high level of information transparency and visibility can increase the overall supply network's transparency, allowing for better supply chain management and sustainability.

Since the logistics base complexity involves both the core organization's multiple logistics carriers and logistics information complexity, blockchain technology can help the core firm better manage supply chain complexity and improve supply chain sustainability. The problem of reverse logistics should be included in the full product portfolio of products and materials life cycle, which should include recycling, repair, reuse, and renewal [82].

Blockchain technology allows for comprehensive clarification and documentation of this information. The transparency and accountability of the information provided by blockchain enable managers to compare their energy consumption and reusability of their products with other similar entities in the market, assess logistics complexity on time, to better manage negative logistics complexity, and make better use of logistics complexity and enhance supply chain sustainability.

Through the above analysis, we propose the following:

H2: utilizing blockchain technology can help manage the logistics base complexity to enhance supply chain sustainability.

4.2.3. The Relationship between Blockchain Technology and Customer Base Complexity. Blockchain technology connects downstream supply chain members, including retailers and customers, and transparency of information enables core enterprises to track product sales performance, and data can be used by all supply chain members, in which way potential difficulties in product demand and use can be observed not only by multiple members of the supply chain but also by multiple members of the supply chain, which may limit uncertainty and related issues. Blockchain is a comprehensive technology that connects end-customers with upstream suppliers, and customer claims can be recorded on blockchain ledgers where upstream suppliers can see information about those customers [81].

Applying blockchain technology to the supply chain can provide real information about market and product quality, as well as customer satisfaction and expectations. Customer demand differentiation is an important aspect of managing supply chain complexity, while customer base complexity is the most critical customer demand. Blockchain technology can provide supply chain demand visibility from the supply side to the demand side. This results in the management of the demand chain, where end-customer demand information is visible among all partners, and blockchain technology provides flexibility for supply chain management to reduce delays and risks in the supply chain [82]. By using blockchain technology to accurately predict demand in the supply chain, inventory costs in the supply chain can be reduced, the risk of supply chain disruption can be alleviated, and the problem of client complexity and sustainability in the supply chain can be improved.

Through the above analysis, we propose the following:

> H3: utilizing blockchain technology can help manage the customer base complexity to enhance supply chain sustainability.

The third question is answered by the three hypotheses stated above. The purpose of this study is to figure out how blockchain technology affects supply chain complexity. By use of blockchain to enable information and relationship governance is a key approach to dealing with the supply chain's complexity. Supply network complexity is a critical component in obtaining survival and development opportunities for supply network firms. Supply network complexity influences both external and internal organizational change and has a significant impact on achieving continual performance optimization. A network organization's ability to manage the complexity of its supply network and adapt rapidly to the complexity of the external environment is critical to its existence. As a result, an organization's competitiveness is solely determined by its capacity to manage complexity.

In sum, we mainly put forward three hypotheses about the relationship between blockchain technology and supply chain complexity. The hypotheses proposed in this study are summarized in Table 1.

5. Blockchain Technology as a Management Response to the Supply Network Complexity

This section summarizes the previous discussion of descriptive frameworks for understanding supply chain complexity management. In the first part, we draw on the study of Maylor and Turner [83], which provides a corresponding approach to the three dimensions of supply chain complexity, Maylor and Turner [83] divide supply chain complexity into three dimensions: structural dimension, socio-political dimension, and emergent dimension, where the response consists of three dimensions: planning and control, relationship development, and flexibility. The study's second section mostly relies on ambidexterity research to demonstrate how firms can leverage existing information or build and explore new knowledge to minimize supply chain complexity or adapt to it. From an exploitation standpoint, complexity can be reduced or eliminated by using appropriately known technologies, processes, or best practices; from an exploration standpoint, complexity can be reduced or eliminated by developing or introducing a new solution, and in response to supply network complexity. The benefits of complexity can be obtained from an existing solution, and the benefits of complexity can be obtained from a development perspective. Taking advantage of complexity that competitors cannot emulate.

In the area of organizational learning, March [84] proposes activities that utilize (refine and use existing knowledge) and develop (innovation, problem-solving, and drilling new knowledge), both of which compete with each other for limited organizational resources within the organization. Subsequent studies of trade-offs between development and exploitation led to a great deal of research on ambidexterity. Ambidexterity is also an important area of research in the supply chain, and some studies have shown that supply chain ambidexterity contributes to business performance, interorganizational relationships, and flexibility [85, 86]. Despite the fact that ambidexterity research has become a useful perspective for analyzing supply network performance and ambidexterity, few studies employ it to understand supply chain complexity.

Supply chain complexity has become a prominent research issue in supply chain management; yet, for the time being, the study of complexity has tended to focus on two aspects of complexity: the negative impact of complexity and the positive impact of complexity. Rather than focusing on ways to decrease or expand supply chain complexity, we divided it into two categories in this study: positive and negative. We advocate minimizing (lowering) the impact of negative values for negative valences, and maximizing the impact of complexity for positive valences by adapting or increasing the angle for positive valences. Minimization is used to cope with negative complexity, while adaptation is used to deal with positive complexity. Both ways can answer using an ambidexterity viewpoint (exploration and exploitation). Systems and processes can be put in place to help limit the impact of supply chain complexity when adopting blockchain technology as a response (which answers the fourth question). Figure 5 is our proposed ambidexterity management of supply network complexity by using blockchain technology.

Blockchain technology can be used to respond to the positive and negative valence of supply network complexity from the perspective of ambidexterity. On the one hand, blockchain technology can be used for exploitation activities to improve the function of positive valence, that is, using blockchain technology to benefit from the supply network's complexity and optimize the organizational structure. To increase supply chain members' ability to respond to supply network disruption concerns, use blockchain technology to manage supply chain members' relationships, and to facilitate collaboration among supply chain members. Also, make use of the data offered by blockchain technology to improve present products and services, as well as the current state of operations. On the other hand, blockchain technology can be used for exploration activities; that is, blockchain technology can be used in novel ways, leveraging the benefits of complexity to generate competitive

Table 1: The relationship between blockchain technology and supply chain complexity.

Number	Hypotheses description
H1	Utilizing blockchain technology can help manage the supply base complexity to enhance supply chain sustainability
H2	Utilizing blockchain technology can help manage the logistics base complexity to enhance supply chain sustainability
H3	Utilizing blockchain technology can help manage the customer base complexity to enhance supply chain sustainability

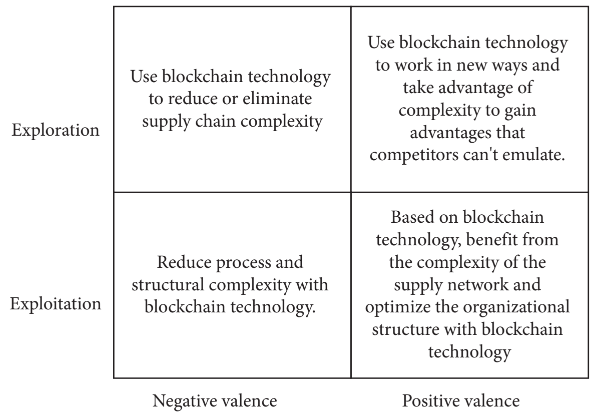


Figure 5: Ambidexterity management of the supply network complexity by using blockchain technology.

advantages that are difficult to duplicate. Blockchain technology is being used to organize resources to create value for supply chain organizations, strengthen their strategic advantage, and harness the market and customers supplied by blockchain technology to produce new products or deliver new services.

On the one hand, blockchain technology can be used to alleviate the negative valence of supply network complexity; that is, blockchain technology can be used to lessen process and structural complexity. For example, using blockchain technology to design and apply controls to describe the complexity of the negative impact would be a good example. The use of blockchain technology to efficiently coordinate production and logistics activities, as well as the use of blockchain technology to quickly explain to consumers the cause of supply network disruption and the status of supply network recovery; On the other hand, blockchain technology can be utilized in exploration activities to minimize or eliminate the negative valence effect. Using blockchain technology's transparency to respond flexibly to demand fluctuations and using blockchain technology to identify potentially problematic suppliers, carriers, and dishonest customers.

6. Conclusion

The previous study suggests that supply chain complexity can be negative to the supply chain performance, and some studies indicate that supply chain complexity can be positive to help the supply chain to improve the ability to cope with supply chain risks. To explore this question, we mainly use valence theory to divide supply chain complexity into positive valence and negative valence. Based on the previous analysis, we divide the supply network's complexity into three categories: supply base complexity, logistics base complexity, and customer base complexity. We also presented three hypotheses on the relationship between blockchain technology and supply network complexity. Then, according to the valence framework, the beneficial and detrimental features of the supply network's complexity are summarized as positive and negative valences. Simultaneously, the ambidexterity theory is discussed, as well as how to examine and apply activities to deal with the supply chain complexity of positive and negative valences using blockchain technology.

Through a systematic analysis, we show that blockchain technology in supply chain management may achieve the most crucial function of trusted transparency. Blockchain, as a governance mechanism, is often able to better understand partner activities and minimize supply chain risk by investing in emerging supply chain transparency technologies [35, 36]. Deploying technologies related to supply chain transparency, helps companies reduce search costs, and improve their reputation. The study by Lamming et al. [87] shows that different degrees of information sharing within the supply chain provides all participants with the knowledge, product source, and process information.

With the help of ambidexterity theory, using blockchain technology, the positive and negative aspects of supply chain complexity are examined and leveraged. Exploration and exploitation activities can both benefit from blockchain technology. To utilize ambidexterity by dealing with the negative valence of supply chain complexity, blockchain technology is being used to reduce process and structural complexity. The application of blockchain technology to simplify processes and structures and efficiently organize production and logistics activities; customers can be informed about the reasons for supply network disruptions and the progress of supply network recovery using blockchain technology. Employing blockchain technology to decrease or eliminate complexity while exploring features of ambidexterity, seek new suppliers, logistics carriers, and customers; identify potentially dangerous suppliers, carriers, and dishonest customers, and respond quickly to changing requirements with transparent information given by blockchain technology.

By employing ambidexterity in dealing with the positive valence of supply network complexity: Benefit from supply network complexity, use blockchain technology to optimize the organizational structure and use blockchain technology to manage relationships among supply chain members, facilitating collaboration among supply chain members and improving their ability to respond to the supply network disruption risk. Make use of the data offered by blockchain technology to improve current products and services, as well as existing operations. For the investigation of ambidexterity disruption, by employing blockchain technology to work in new ways, the benefits of complexity to acquire competitive advantages that are difficult to duplicate; developing new products or providing new services using blockchain technology's marketplaces and customers.

From the above-given analysis, we can infer that blockchain technology can help manage the supply network complexity and draw on ambidexterity theory to deal with positive and negative aspects of supply network complexity, which may help to solve marketing issues that the marketing issues are related to the supply chain management, the higher the level of supply chain management is, the more beneficial it is to the marketing of firms.

7. Implications and Directions for Future Research

7.1. Theoretical Significance. First, we divide supply network complexity into three categories: supply base complexity, logistics base complexity, and customer base complexity, supply base complexity refers to the number of suppliers, degree of difference among providers, and interrelationships among suppliers. Customer base complexity is usually dependent on the number of customers and product categories, whereas logistics base complexity relates to a supply network with a large number of carriers, where carriers indicate the network's connectivity condition; second, we use the valence framework theory to synthesize the dual characteristics of supply network complexity into positive and negative valences, to widen the applicability of the valence theory. The two sides of how to deal with the complexity of the supply network are investigated from the standpoint of exploitation and exploration, which enriches the research on the complexity of the supply network based on the ambidexterity theory.

Third, we synthesize the dual characteristics of supply network complexity into positive and negative valences and expand the application of the valence theory using the valence framework theory. These two sides of how to cope with supply network complexity are explored from the standpoints of exploitation and exploration, which contributes to the complexity of supply network research. This is one of the few studies that will use blockchain technology to do exploration and exploitation activities to deal with positive valence and negative valence of supply network complexity based on ambidexterity theory. This study also expands the application scenarios of ambidexterity theory and valence theory.

7.2. Practical Significance. This is the first study to propose the use of blockchain technology to manage supply network complexity, and it can provide some guidance for firms exploring blockchain implementation. By introducing blockchain technology into the supply chain, the supply chain's transparency might be greatly improved. Most notably, the most significant advantage of blockchain technology beyond other technologies is the achievement of trusted transparency of information on the supply chain. This study divides supply network complexity into supply base complexity, logistics base complexity, and customer base complexity, which can help managers better manage supply network complexity, and it divides the effects of supply chain network complexity into positive and negative valences, reconciling the previous study of supply network complexity into a single negative or positive study. It can give managers some direction on how to manage the supply network's complexity.

7.3. Limitations and Future Research Directions. This study also has some limitations. First, the hypothesis in this study has yet to be empirically validated, and further research will be required to demonstrate the validity of this research methodology using data. Second, there are several methods for classifying supply network complexity. In some studies, supply network complexity is classified as detail complexity and dynamic complexity, whereas in others, it is classified as upstream complexity, downstream complexity, and internal complexity. As a result, more innovative classification methods may be developed in the future. Finally, supply network complexity management can be combined with other emerging technologies in the future to demonstrate how new technologies can be utilized to regulate supply network complexity.

In conclusion, this paper contributes to the field of supply network complexity research by investigating the relationship between blockchain technology and supply network complexity, as well as presenting a new research perspective for supply network complexity management based on valence theory and ambidexterity theory.

Data Availability

The data used to support the study are included in the paper.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by the Scientific Research Foundation of Yunnan Education Department in 2022 under Projects No. 2022Y481.

References

[1] Z. Yu, A. Razzaq, A. Rehman, A. Shah, K. Jameel, and R. S. Mor, "Disruption in global supply chain and socio-economic shocks: a lesson from COVID-19 for sustainable production and consumption," *Operations Management Research*, pp. 1–16, 2021.

[2] G. M. Magableh, "Supply chains and the COVID-19 pandemic: a comprehensive framework," *European Management Review*, vol. 18, no. 3, pp. 363–382, 2021.

[3] M. A. Ateş, R. Suurmond, D. Luzzini, and D. Krause, "Order from chaos: a meta-analysis of supply chain complexity and firm performance," *Journal of Supply Chain Management*, vol. 58, no. 1, pp. 3–30, 2021.

[4] X. Zhao, K. M. Ismail, and K. M. Carley, "Organizational design and restructuring in response to crises: lessons from computational modeling and real-world cases," *Organization Science*, vol. 17, no. 5, pp. 598–618, 2006.
[5] C. Perrow, *Normal Accidents*, Princeton university press, Princeton, NJ, U.S.A, 2011.
[6] C. Perrow, "Normal accidents. Living with high-risk technologies," *Normale Katastrophen. Die unvermeidbaren Risiken der Grosstechnik*, vol. 102800, 1988.
[7] Y. Kayikci, D. Durak Usar, and B. L. Aylak, "Using blockchain technology to drive operational excellence in perishable food supply chains during outbreaks," *International Journal of Logistics Management*, 2021.
[8] D. M. Lambert and M. G. Enz, "Issues in supply chain management: progress and potential," *Industrial Marketing Management*, vol. 62, pp. 1–16, 2017.
[9] Y. Chen, S. Ding, Z. Xu, H. Zheng, and S. Yang, "Blockchain-based medical records secure storage and medical service framework," *Journal of Medical Systems*, vol. 43, no. 1, pp. 5–9, 2019.
[10] K. R. Lakhani and M. Iansiti, "The truth about blockchain," *Harvard Business Review*, vol. 95, no. 1, pp. 119–127, 2017.
[11] U. Ramanathan and A. Gunasekaran, "Supply chain collaboration: impact of success in long-term partnerships," *International Journal of Production Economics*, vol. 147, pp. 252–259, 2014.
[12] Q. Lu, M. Goh, and R. De Souza, "An empirical investigation of swift trust in humanitarian logistics operations," *The Palgrave Handbook of Humanitarian Logistics and Supply Chain Management*, vol. 8, pp. 279–296, 2018.
[13] Y. Xiong, H. K. S. Lam, A. Kumar, E. W. T. Ngai, C. Xiu, and X. Wang, "The mitigating role of blockchain-enabled supply chains during the COVID-19 pandemic," *International Journal of Operations & Production Management*, vol. 41, no. 9, pp. 1495–1521, 2021.
[14] P. Xu, J. Lee, J. R. Barth, and R. G. Richey, "Blockchain as supply chain technology: considering transparency and security," *International Journal of Physical Distribution & Logistics Management*, vol. 51, no. 3, pp. 305–324, 2021.
[15] A. Sheel and V. Nath, "Effect of blockchain technology adoption on supply chain adaptability, agility, alignment and performance," *Management Research Review*, vol. 42, no. 12, pp. 1353–1374, 2019.
[16] Y. Cui and H. Idota, "Improving supply chain resilience with establishing A decentralized information sharing mechanism," in *Proceedings of the 5th Multidisciplinary International Social Networks Conference on - MISNC '18*, pp. 1–7, Saint-Etienne, France, June 2018.
[17] M. Vivaldini and P. R. de Sousa, "Blockchain connectivity inhibitors: weaknesses affecting supply chain interaction and resilience," *Benchmarking: An International Journal*, vol. 28, no. 10, pp. 3102–3136, 2021.
[18] M. Alazab, S. Alhyari, A. Awajan, and A. B. Abdallah, "Blockchain technology in supply chain management: an empirical study of the factors affecting user adoption/acceptance," *Cluster Computing*, vol. 24, no. 1, pp. 83–101, 2020.
[19] A. Kumar, R. Liu, and Z. Shan, "Is blockchain a silver bullet for supply chain management? Technical challenges and research opportunities," *Decision Sciences*, vol. 51, no. 1, pp. 8–37, 2020.
[20] S. Tönnissen and F. Teuteberg, "Analysing the impact of blockchain-technology for operations and supply chain management: an explanatory model drawn from multiple case studies," *International Journal of Information Management*, vol. 52, Article ID 101953, 2020.
[21] A. Rejeb, J. G. Keogh, S. J. Simske, T. Stafford, and H. Treiblmaier, "Potentials of blockchain technologies for supply chain collaboration: a conceptual framework," *International Journal of Logistics Management*, vol. 32, no. 3, pp. 973–994, 2021.
[22] H. R. Vandchali, S. Cahoon, and S. L. Chen, "The impact of supply chain network structure on relationship management strategies: an empirical investigation of sustainability practices in retailers," *Sustainable Production and Consumption*, vol. 28, pp. 281–299, 2021.
[23] M. Nakano and K. Matsuyama, "The relationship between internal supply chain structure and operational performance: survey results from Japanese manufacturers," *Supply Chain Management: International Journal*, vol. 27, no. 4, pp. 469–484, 2021.
[24] T. Randall and K. Ulrich, "Product variety, supply chain structure, and firm performance: analysis of the U.S. Bicycle industry," *Management Science*, vol. 47, no. 12, pp. 1588–1604, 2001.
[25] M. B. C. Menezes, D. R. Hernández, and Y. T. Chen, "On the validity and practical relevance of a measure for structural complexity," *International Journal of Production Economics*, vol. 240, Article ID 108243, 2021.
[26] E. K. Anin, N. Boso, and D. Asamoah, "Moderating effect of supply chain complexity in governance mechanisms and operational performance relationship: evidence from a sub-Saharan African market," *Africa Journal of Management*, vol. 7, pp. 1–23, 2021.
[27] P. F. Skilton and J. L. Robinson, "Traceability and normal accident theory: how does supply network complexity influence the traceability of adverse events?" *Journal of Supply Chain Management*, vol. 45, no. 3, pp. 40–53, 2009.
[28] Y. Dong, K. Skowronski, S. Song, S. Venkataraman, and F. Zou, "Supply base innovation and firm financial performance," *Journal of Operations Management*, vol. 66, no. 7-8, pp. 768–796, 2020.
[29] T. Y. Choi and D. R. Krause, "The supply base and its complexity: implications for transaction costs, risks, responsiveness, and innovation," *Journal of Operations Management*, vol. 24, no. 5, pp. 637–652, 2005.
[30] R. Wiedmer, Z. S. Rogers, M. Polyviou, C. Mena, and S. Chae, "The dark and bright sides of complexity: a dual perspective on supply network resilience," *Journal of Business Logistics*, vol. 42, no. 3, pp. 336–359, 2021.
[31] C. C. Bozarth, D. P. Warsing, B. B. Flynn, and E. J. Flynn, "The impact of supply chain complexity on manufacturing plant performance," *Journal of Operations Management*, vol. 27, no. 1, pp. 78–93, 2009.
[32] J. P. Peter, "A comparative analysis of three consumer decision strategies," *Journal of Consumer Research*, vol. 2, no. 1, pp. 29–37, 1975.
[33] D. J. Kim, D. L. Ferrin, and H. R. Rao, "A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents," *Decision Support Systems*, vol. 44, no. 2, pp. 544–564, 2008.
[34] T. Y. Choi, S. Narayanan, D. Novak, J. Olhager, J. B. Sheu, and F. Wiengarten, "Managing extended supply chains," *Journal of Business Logistics*, vol. 42, no. 2, pp. 200–206, 2021.
[35] G. M. Hastig and M. S. Sodhi, "Blockchain for supply chain traceability: business requirements and critical success factors," *Production and Operations Management*, vol. 29, no. 4, pp. 935–954, 2020.

[36] M. Montecchi, K. Plangger, and M. Etter, "It's real, trust me! Establishing supply chain provenance using blockchain," *Business Horizons*, vol. 62, no. 3, pp. 283–293, 2019.
[37] K. S. Hald and A. Kinra, "How the blockchain enables and constrains supply chain performance," *International Journal of Physical Distribution & Logistics Management*, vol. 49, no. 4, pp. 376–397, 2019.
[38] W. Yin and W. Ran, "Theoretical exploration of supply chain viability utilizing blockchain technology," *Sustainability*, vol. 13, no. 15, p. 8231, 2021.
[39] A. K. Gupta, S. P. Raj, and D. Wilemon, "A model for studying R&D-Marketing interface in the product innovation process," *Journal of Marketing*, vol. 50, no. 2, pp. 7–17, 1986.
[40] P. Kumar, N. Langberg, and D. Zvilichovsky, "Crowdfunding, financing constraints, and real effects," *Management Science*, vol. 66, no. 8, pp. 3561–3580, 2020.
[41] H. Treiblmaier, "The impact of the blockchain on the supply chain: a theory-based research framework and a call for action," *Supply Chain Management: International Journal*, vol. 23, no. 6, pp. 545–559, 2018.
[42] E. Brynjolfsson and A. McAfee, *The Second Machine Age: Work, Progress, and prosperity in a Time of Brilliant Technologies*, WW Norton & Company, New York, NY, USA, 2014.
[43] C. Bode and S. M. Wagner, "Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions," *Journal of Operations Management*, vol. 36, no. 1, pp. 215–228, 2015.
[44] G. Y. Gao, E. Xie, and K. Z. Zhou, "How does technological diversity in supplier network drive buyer innovation? Relational process and contingencies," *Journal of Operations Management*, vol. 36, no. 1, pp. 165–177, 2015.
[45] I. Giannoccaro, A. Nair, and T. Choi, "The impact of control and complexity on supply network performance: an empirically informed investigation using NK simulation analysis," *Decision Sciences*, vol. 49, no. 4, pp. 625–659, 2018.
[46] G. Lu and G. Shang, "Impact of supply base structural complexity on financial performance: roles of visible and not-so-visible characteristics," *Journal of Operations Management*, vol. 53-56, no. 1, pp. 23–44, 2017.
[47] M. A. Bellamy, S. Ghosh, and M. Hora, "The influence of supply network structure on firm innovation," *Journal of Operations Management*, vol. 32, no. 6, pp. 357–373, 2014.
[48] J. Aitken, C. Bozarth, and W. Garn, "To eliminate or absorb supply chain complexity: a conceptual model and case study," *Supply Chain Management: International Journal*, vol. 21, no. 6, pp. 759–774, 2016.
[49] M. Chen, H. Liu, S. Wei, and J. Gu, "Top managers' managerial ties, supply chain integration, and firm performance in China: a social capital perspective," *Industrial Marketing Management*, vol. 74, pp. 205–214, 2018.
[50] H. Lorentz, J. Töyli, T. Solakivi, H. M. Hälinen, and L. Ojala, "Effects of geographic dispersion on intra-firm supply chain performance," *Supply Chain Management: International Journal*, vol. 17, no. 6, pp. 611–626, 2012.
[51] R. Rossiter and A. M. Knemeyer, "Controlling for logistics complexity: scale development and validation," *International Journal of Logistics Management*, vol. 20, no. 2, pp. 187–200, 2009.
[52] C. Bode and J. R. Macdonald, "Stages of supply chain disruption response: direct, constraining, and mediating factors for impact mitigation," *Decision Sciences*, vol. 48, no. 5, pp. 836–874, 2017.
[53] H. Yu, A. Z. Zeng, and L. Zhao, "Single or dual sourcing: decision-making in the presence of supply chain disruption risks," *Omega*, vol. 37, no. 4, pp. 788–800, 2009.
[54] C. S. Tang, "Robust strategies for mitigating supply chain disruptions," *International Journal of Logistics Research and Applications*, vol. 9, no. 1, pp. 33–45, 2006.
[55] Y. Park, P. Hong, and J. J. Roh, "Supply chain lessons from the catastrophic natural disaster in Japan," *Business Horizons*, vol. 56, no. 1, pp. 75–85, 2013.
[56] T. Xiao and X. Qi, "Price competition, cost and demand disruptions and coordination of a supply chain with one manufacturer and two competing retailers," *Omega*, vol. 36, no. 5, pp. 741–753, 2008.
[57] A. Arshinder, A. Kanda, and S. G. Deshmukh, "Supply chain coordination: perspectives, empirical studies and research directions," *International Journal of Production Economics*, vol. 115, no. 2, pp. 316–335, 2008.
[58] J. Olhager, "The role of the customer order decoupling point in production and supply chain management," *Computers in Industry*, vol. 61, no. 9, pp. 863–868, 2010.
[59] M. Montecchi, K. Plangger, and D. C. West, "Supply chain transparency: a bibliometric review and research agenda," *International Journal of Production Economics*, vol. 238, Article ID 108152, 2021.
[60] N. Kumar and A. Yakhlef, "Managing business-to-business relationships under conditions of employee attrition: a transparency approach," *Industrial Marketing Management*, vol. 56, pp. 143–155, 2016.
[61] T. Hammervoll and E. Bø, "Shipper-carrier integration," *European Journal of Marketing*, vol. 44, no. 7/8, pp. 1121–1139, 2010.
[62] K. Bailey and M. Francis, "Managing information flows for improved value chain performance," *International Journal of Production Economics*, vol. 111, no. 1, pp. 2–12, 2008.
[63] E. Brandon-Jones, B. Squire, C. W. Autry, and K. J. Petersen, "A contingent resource-based perspective of supply chain resilience and robustness," *Journal of Supply Chain Management*, vol. 50, no. 3, pp. 55–73, 2014.
[64] N. Osadchiy, V. Gaur, and S. Seshadri, "Systematic risk in supply chain networks," *Management Science*, vol. 62, no. 6, pp. 1755–1777, 2016.
[65] M. S. Sodhi and C. S. Tang, "Research opportunities in supply chain transparency," *Production and Operations Management*, vol. 28, no. 12, pp. 2946–2959, 2019.
[66] B. Kalkanci and E. L. Plambeck, "Managing supplier social and environmental impacts with voluntary versus mandatory disclosure to investors," *Management Science*, vol. 66, no. 8, pp. 3311–3328, 2020.
[67] Y. H. Kim and G. F. Davis, "Challenges for global supply chain sustainability: evidence from conflict minerals reports," *Academy of Management Journal*, vol. 59, no. 6, pp. 1896–1916, 2016.
[68] A. Ghosh and J. Fedorowicz, "The role of trust in supply chain governance," *Business Process Management Journal*, vol. 14, no. 4, pp. 453–470, 2008.
[69] L. Koh, A. Dolgui, and J. Sarkis, "Blockchain in Transport and Logistics–Paradigms and Transitions," *International Journal of Production Research*, vol. 58, no. 7, pp. 2054–2062, 2020.
[70] D. Tapscott and A. Tapscott, "How blockchain will change organizations," *MIT Sloan Management Review*, vol. 58, no. 2, p. 10, 2017.
[71] P. P. Datta and M. G. Christopher, "Information sharing and coordination mechanisms for managing uncertainty in supply

chains: a simulation study," *International Journal of Production Research*, vol. 49, no. 3, pp. 765–803, 2011.

[72] S. Maheshwari, P. Gautam, and C. K. Jaggi, "Role of big data analytics in supply chain management: current trends and future perspectives," *International Journal of Production Research*, vol. 59, no. 6, pp. 1875–1900, 2021.

[73] V. K. Manupati, T. Schoenherr, M. Ramkumar, S. M. Wagner, S. K. Pabba, and R. Inder Raj Singh, "A blockchain-based approach for a multi-echelon sustainable supply chain," *International Journal of Production Research*, vol. 58, no. 7, pp. 2222–2241, 2020.

[74] D. Macrinici, C. Cartofeanu, and S. Gao, "Smart contract applications within blockchain technology: a systematic mapping study," *Telematics and Informatics*, vol. 35, no. 8, pp. 2337–2354, 2018.

[75] A. Dolgui, D. Ivanov, S. Potryasaev, B. Sokolov, M. Ivanova, and F. Werner, "Blockchain-oriented dynamic modelling of smart contract design and execution in the supply chain," *International Journal of Production Research*, vol. 58, no. 7, pp. 2184–2199, 2020.

[76] Z. A. Collier and J. Sarkis, "The zero trust supply chain: managing supply chain risk in the absence of trust," *International Journal of Production Research*, vol. 59, no. 11, pp. 3430–3445, 2021.

[77] L. W. Wong, G. W. H. Tan, V. H. Lee, K. B. Ooi, and A. Sohal, "Unearthing the determinants of Blockchain adoption in supply chain management," *International Journal of Production Research*, vol. 58, no. 7, pp. 2100–2123, 2020.

[78] X. Xu, M. Zhang, G. Dou, and Y. Yu, "Coordination of a supply chain with an online platform considering green technology in the blockchain era," *International Journal of Production Research*, pp. 1–18, 2021.

[79] Y. Chang, E. Iakovou, and W. Shi, "Blockchain in global supply chains and cross border trade: a critical synthesis of the state-of-the-art, challenges and opportunities," *International Journal of Production Research*, vol. 58, no. 7, pp. 2082–2099, 2020.

[80] P. Helo and A. H. M. Shamsuzzoha, "Real-time supply chain-A blockchain architecture for project deliveries," *Robotics and Computer-Integrated Manufacturing*, vol. 63, Article ID 101909, 2020.

[81] Y. Wang, C. H. Chen, and A. Z. Sales, "Designing a blockchain enabled supply chain," *International Journal of Production Research*, vol. 59, no. 5, pp. 1450–1475, 2021.

[82] K. Wust and A. Gervais, "Do you need a blockchain?" in *Proceedings of the 2018 Crypto Valley Conference on Blockchain Technology (CVCBT)*, Zug, Switzerland, June 2018.

[83] H. Maylor and N. Turner, "Understand, reduce, respond: project complexity management theory and practice," *International Journal of Operations & Production Management*, vol. 37, no. 8, pp. 1076–1093, 2017.

[84] J. G. March, "Exploration and exploitation in organizational learning," *Organization Science*, vol. 2, no. 1, pp. 71–87, 1991.

[85] R. A. Eltantawy, "The role of supply management resilience in attaining ambidexterity: a dynamic capabilities approach," *Journal of Business & Industrial Marketing*, vol. 31, no. 1, pp. 123–134, 2016.

[86] C. Blome, T. Schoenherr, and D. Rexhausen, "Antecedents and enablers of supply chain agility and its effect on performance: a dynamic capabilities perspective," *International Journal of Production Research*, vol. 51, no. 4, pp. 1295–1318, 2013.

[87] R. C. Lamming, N. D. Caldwell, D. A. Harrison, and W. Phillips, "Transparency in supply relationships: concept and practice," *Journal of Supply Chain Management*, vol. 37, no. 3, pp. 4–10, 2001.

Hindawi
Complexity
Volume 2022, Article ID 4402673, 12 pages
https://doi.org/10.1155/2022/4402673

Research Article

Effects of Organizational Culture on Employer Attractiveness of Hotel Firms: Topic Modeling Approach

Kyoung-Joo Lee [1] and Sun-Yong Choi [2]

[1] *Department of Tourism Management, Gachon University, Seongnam, Gyeonggi 13120, Republic of Korea*
[2] *Department of Financial Mathematics, Gachon University, Seongnam, Gyeonggi 13120, Republic of Korea*

Correspondence should be addressed to Sun-Yong Choi; sunyongchoi@gachon.ac.kr

Received 21 January 2022; Accepted 9 May 2022; Published 30 May 2022

Academic Editor: Ning (Chris) Chen

As the acquisition and retention of motivated and skilled employees are key to the high performance of hotel firms, employer attractiveness of hotel firms is a critical factor in achieving competitive advantage. Focusing on organizational culture, this study analyzes how different cultural attributes affect hotel firms' attractiveness as employers. For the empirical analysis, this study collected 54,040 reviews of 157 large hotel chains and firms from Glassdoor in the United States. This study combines an unsupervised machine learning tool for topic modeling (latent Dirichlet allocation) with the coding process of researchers to measure the different cultural attributes of hotel firms. The research results show the positive and significant impact of four cultural attributes—collaborative, employee development, fair compensation, and customer focus—on employer attractiveness measured by both users' employer satisfaction and recommendations to friends. In contrast, an innovation culture has no significant effect on attractiveness.

1. Introduction

The goal of this research is to analyze the influence of organizational culture on hotel firms' employer attractiveness. According to the Bureau of Labor Statistics in the United States, the employee turnover rate in the hospitality industry was 78.9% in 2019, while the national average turnover rate was 36.4%. The hospitality industry has been dealing with chronic turnover problems caused by high job strain, role stressors, and emotional labor. As a result, the acquisition and retention of skilled human resources is an essential condition for gaining a competitive advantage in the hospitality industry. [1, 2]. Given these issues, improving employer attractiveness is an important responsibility of hotel management to win against competitors. Employer attractiveness refers to an organization's image and perception as an employer based on the evaluation of the employment value and benefits offered by the organization [3–5].

Although researchers have long implied the potential influence of organizational culture on employer attractiveness (Sheridan [6]; Lievens and Highhouse [7]; Chhabra and Sharma [4]; and Theurer et al. [5]), no prior research has analyzed the influence of organizational culture on hotels' attractiveness as an employer. This study aims to fill this gap in the existing literature and investigates the impact of diverging attributes of organizational culture on hotels' employer attractiveness, based on the topic modeling of big employer review data.

Organizational culture, as a prominent characteristic of successful organizations, plays a critical role in developing and maintaining employees' dedication and commitment to an organization [8–10]. Organizational culture is a set of shared values, beliefs, customs, and assumptions that define employees' perceptions, thinking, and behavior in their work and coping with problems [8–10]. Organizational culture is a shared pattern of basic assumptions invented, discovered, or developed by leaders and organizational members to deal with the problems of external adaptation and internal integration [10]. Once organizational members have learned how to hold common assumptions and beliefs, organizational culture generates common perceiving, thinking, and behaving patterns, which provide organizational members with meaning, stability, and comfort [10]. Governing the employees' perceptions, the different attributes of organizational culture define how an organization conducts its business and becomes valuable, inimitable, and rare resources to determine organizational performance [8]. In hotel services, organizational culture directly affects the policies, practices, and procedures of employees' activities, all of which have a significant bearing on service quality and customer satisfaction [11–13]

This study generates theoretical predictions about how different attributes of organizational culture affect hotel firms' employer attractiveness and constructs big data of employee reviews to overcome the limitations of traditional survey methods. It adopts a topic modeling tool to measure and test the influence of organizational culture based on text data.

First, existing hospitality studies on organizational culture have examined a relatively narrow scope of outcomes, such as the identification of different dimensions of organizational culture [14–17], an investigation of its influence on employee behavior ([18, 19]Li and Huang [12]; Kang et al. [20]; and Kang and Busser [13]), and an analysis of the impact on organizational performance [21, 22]. Highlighting the problems of employee retention in hotels, this study focuses on employer attractiveness as a critical result of hotel firms' organizational culture.

Second, to empirically analyze the impact of organizational culture on employer attractiveness, this study collected employees' review data in Glassdoor, the largest job-searching platform in the United States [23], constructed a sample dataset of 54,040 reviews from 157 hotel firms, and developed a language-based measurement of organizational culture [23].

Third, to measure cultural attributes in hotel firms, this study adopts the topic modeling tool of latent Dirichlet allocation (LDA; Blei [24]; Maier et al. [25]; Corritore et al. [23]). The topic modeling approach helps researchers identify the hidden structure of documents by showing interpretable topics, and LDA reports the cultural attributes by generating a probability distribution of cultural topics in the employees' review data (Blei [24]; Maier et al. [25]; Corritore et al. [23]). By combining the unsupervised machine learning of LDA and the researchers' coding process, this study assesses the different cultural attributes of hotel firms and analyzes their impact on employer attractiveness measured by both "employer satisfaction" and "employee's recommendation to friends."

Advancing the existing studies on the organizational culture of hotels and employer attractiveness, this study proposes a new methodological approach beyond the traditional self-reporting survey using a large-scale dataset of employee reviews and the application of machine learning tools.

2. Literature Review

Existing studies on organizational culture in hospitality have a relatively long history, and the major literature has not only focused on identifying different dimensions of organizational culture and scale development (Bellou and Andronikidis [14]; Dawson et al. [15]; Bavik [16]; Datta and Singh [17]), but also on their influence on employee behavior (Tepeci and Bartlett [18]; Yang [19]; Li and Huang [12]; Kang et al. [20]; Kang and Busser [13]) and organizational performance (He et al. [21]; del Rosario et al. [22]).

2.1. Identification of Culture Dimensions. One significant aspect of organizational culture research in hospitality is the effort to identify cultural attributes and develop scales to measure them. Given that an accurate understanding of the prevalent organizational climate helps optimize service performance by identifying organizational strengths and weaknesses, Bellou and Andronikidis [14] proposed and measured 17 dimensions of the organizational climate based on a survey of 217 hotel employees in Greece. Dawson et al. [15] tried to identify both a measurably distinctive hospitality industry culture and personal attributes to facilitate the culture-person matching process. Based on a survey of 741 employees in various hospitality sectors in the United States, the authors identified four valid dimensions of organizational culture. With the goal of identifying distinguishable organizational cultures in the hospitality industry, Bavik [16] conducted 18 interviews and a survey of 281 hotel employees in New Zealand, generating nine dimensions of organizational culture. To help hotels improve their organizational climate, Datta and Singh [17] clarified four dimensions based on a survey of 504 hotel employees in India.

2.2. Employee Outcomes. As organizational culture significantly affects employee behaviors, researchers have performed empirical analyses on how different cultural attributes influence a variety of positive employee outcomes. Based on a survey of 182 hospitality management students with hospitality jobs in the United States, Tepeci and Bartlett [18] investigated the influence of organizational culture, individual values, and fit between two dependent variables, such as job satisfaction, intention to quit, and recommendation of the organization. The author found that organizational culture had a positive effect on job satisfaction. Given the significance of effective knowledge management in hotels, Yang [19] analyzed the influence of organizational culture on knowledge-sharing behavior. A survey of 1,200 hotel employees in Taiwan showed that collaborative culture has a significant effect on knowledge-sharing behavior. Based on a survey of 500 restaurant employees in China, Li and Songshan [12] found that the service climate has a positive impact on employee performance. Hee et al. [20] also showed the positive influence of service climate on turnover intention based on a survey of 263 casino hotel employees in the United States. Based on a survey of 362 managers and employees in casino hotels in the United States, Hee and Busser [13] found that employee engagement plays a mediating role between service climate and turnover intention while also showing the moderating effect of hierarchy.

2.3. Organizational Outcomes. In addition to employee outcomes, hospitality researchers have investigated how organizational culture affects organizational performance, such as customer satisfaction and innovation. He et al. [21] examined the influence of organizational climate, such as customer orientation, managerial support, and work facilitation, on customer satisfaction based on a survey of 216 hotel employees in China. The same study showed that employee commitment plays a mediating role in the relationship between organizational culture and customer satisfaction. They found that customer orientation has a direct and positive impact on customer satisfaction, whereas managerial support and work facilitation are indirectly associated with customer satisfaction through employee commitment. Given the rapidly increasing environmental significance of the tourism industry, Maria del Rosario et al. [22] presumed organizational culture as an import predictor of eco-innovation in hospitality. They adopted the competing values framework as an analytical model of organizational culture and hypothesized the influence of different organizational cultures such as hierarchy, market, clan, and adhocracy cultures. Based on a survey of 130 hotels in Mexico, they found that clan and adhocracy cultures have a positive and significant effect on hotels' eco-innovations.

2.4. Limitations and New Approach. Although researchers in hospitality studies have long conceptualized cultural attributes and their impact on employee and organizational outcomes, this research finds some restrictions. On the one hand, existing hospitality literature has focused on a relatively restricted scope of employee outcomes, such as employee job satisfaction and turnover intention as well as organizational outcomes, including service satisfaction and innovation performance. However, because it is deeply related to employee satisfaction and dedication to the organization, organizational culture can affect the attractiveness of a hotel firm as an employer to both current and prospective employees.

On the other hand, regarding research methodology, most researchers have relied on employees' self-reported questionnaires, in which few employees' personal perceptions and impressions dominate the assessment of the cultural attributes of an organization [21]. There have been concerns among researchers that the culture survey methodology can compromise the reliability and validity of research results [26]. Addressing the limitations, this study proposes a research model which focuses on employer attractiveness as an important outcome of organizational culture and, for empirical analysis, it introduces a novel methodology of topic modeling analysis using the big review data of current and former employees.

3. Theory and Hypotheses

3.1. Organizational Culture and Employer Attractiveness. Organizational culture is more significant in the service and hospitality industries than in other industries, as it directly affects the policies, practices, and procedures of frontline employees' service activities, informing what is rewarded, supported, and expected in the organization (Glisson [27]; Schneider et al. [11]; Li and Huang [12]; Kang et al. [20]). The attitudes, behaviors, and performance of frontline employees play a crucial role in defining service quality and are strongly influenced by organizational culture (Schneider et al. [11]; Li and Huang [12]; Kang et al. [20]). Rather than management's formal monitoring, cultural norms and values in an organization can more effectively guide, control, and drive employee service behaviors. Organizational culture creates a link between a firm's internal portfolio of resources and capabilities and its external customers [11]. Thus, different attributes of organizational culture lead to considerable variations in employee satisfaction, service quality, and organizational effectiveness [28].

Employer attractiveness refers to the envisioned benefits that current and potential employees perceive when working in a specific organization [4]. Employees and potential applicants develop an organization's image as an attractive employer based on the assessment of the benefits and value provided by the organization (Gehrels and de Looij [3]; Chhabra and Sharma [4]; and Theurer et al. [5]). Understanding and enhancing employer attractiveness is a significant first phase in initiating employer branding strategies. As a systematic human resource management approach, employer branding adopts the branding strategy concept in marketing research and aims to promote the employment image of firms to gain advantage against competitors in the labor market (Gehrels and de Looij [3]; Chhabra and Sharma [4]; and Theurer et al. [5]). As a critical element of employer branding, employer attractiveness provides a competitive advantage in acquiring, nurturing, and retaining talented employees in the competitive labor market.

Hotel firms chronically suffer from a shortage of skilled labor and should make themselves stand out from competitors as attractive employers to win talent (Lievens and Scott [7]). However, this is a huge challenge, because jobs and work within the same industry are very similar (Lievens and Scott [7]). Successful employer branding not only increases the organizational loyalty of current employees but also effectively attracts prospective employees (Gehrels and de Looij [3]; Leekha Chhabra and Sharma [4]; and Theurer et al. [5]). Employer branding is the process of establishing a hotel firm's image as an employer in the labor market (Lievens and Scott [7]; Leekha Chhabra and Sharma [4]). This is a process of communicating what it expects from employees and what it offers to them (Leekha Chhabra and Sharma [4]). Employer attractiveness is the core element of employer branding strategy and is closely associated with varying organizational conditions, such as organizational culture, management style, quality management, and impressions of products or services.

Among the many factors that affect an organization's attractiveness as an employer, organizational culture is one of the most significant (Sheridan [6]; Lievens and Scott [7]; Leekha Chhabra and Sharma [4]; Theurer et al. [5]). An important theme in employer branding literature is the significance of unique organizational attributes that an organization promotes to gain talent (Sheridan [6]; Lievens and Scott [7]; Leekha Chhabra and Sharma [4]; and Theurer et al. [5]). The shared values and norms in an organization strongly influence employees' work and organizational experiences, constitute enduring and distinctive characteristics of the organization, and determine employer attractiveness and brand image for potential applicants. Thus, organizational attributes are the key factors in attracting applicants, and the first positive impression increases the likelihood of an applicant accepting an employment offer (Leekha Chhabra and Sharma [4]).

The critical attributes of organizational culture clarify the uniqueness and distinctiveness of an organization, relative to its competitors, and help prospective employees form a clear idea of the employment value proposed by the organization. Organizational culture determines variations in employee acquisition and retention across organizations in an industry because it fosters varying levels of employees' organizational commitment and loyalty (Sheridan [6]). Favorable attributes of organizational culture enrich employees' work experiences, enhance their organizational commitment and loyalty, and promote career development and growth. Favorable attributes of organizational culture generate a positive image and intensify employer attractiveness for current and prospective employees. Thus, it is predictable that favorable attributes of organizational culture have a positive impact on the employer attractiveness of hotel firms.

3.2. Hypotheses. Among various cultural dimensions, this study focuses on five attributes of organizational culture that have gained relatively wide attention and generated ample discussions in the studies of hospitality organizations. The list includes collaboration, employee development, fair compensation, customer focus, and innovation cultures (Tepeci and Bartlett [18]; Yang [19]; He et al. [21]; Dawson et al. [15]; and Bavik [16]). The following section develops the hypotheses to predict the positive effect of cultural attributes on employer attractiveness.

Collaborative culture emphasizes sharing common vision, mission, and norms of behaviors among organizational members, cares about employees as people, and values collaborative efforts—all of which develop a cohesive and productive workface and enhance organizational commitment (Karl-Erik and Simons [29]; Yang [19]). In this culture, employees regard collaboration and trust as key elements of organizational culture and have a positive attitude toward knowledge sharing and learning from others (Karl-Erik and Simons [29]). Collaborative culture stresses the importance of teamwork and attempts to develop an organizational climate in which employees work well not only within their team but also across different groups, teams, and departments of the organization (Yang [19]). As collaborative culture allows favorable working conditions in which employees develop strong teamwork, cohesion, and commitment, it has a positive impact on the attractiveness of hotel firms as employers.

H1: Collaborative culture has a positive effect on hotel firms' employer attractiveness.

Employee development culture stresses equipping employees with new knowledge and skills and helps them prepare for new job requirements (Lee and Bruvold [30]; Kuvaas and Dysvik [31]). In this culture, organizations emphasize work as a pleasant experience, value human resources, and care about employee growth and development. An employee development culture provides employees with continuous learning opportunities to develop current skills and competencies and gain new ones (Lee and Bruvold [30]; Kuvaas and Dysvik [31]). In this culture, employees can effectively adapt to new changes and achieve high job performance (Lee and Bruvold [30]; Kuvaas and Dysvik [31]). Thus, an employee development culture promotes employees' job satisfaction, affective commitment to the organization (Lee and Bruvold [30]), and intrinsic motivation to service. As employee development culture effectively promotes employee growth and takes care of long-term career plans, it has a positive impact on hotel firms' employer attractiveness.

H2: Employee development culture has a positive effect on hotel firms' employer attractiveness.

Fair compensation culture values norms of fairness in the process and the results of distributive managerial decisions. A fair compensation culture develops employees' perceptions that the organization strongly ensures fairness in the guidelines, policies, and principles to make compensation decisions (Namasivayam et al. [32]). A fair compensation culture provides employees with sufficient value and benefits, significantly promoting employee participation. As it provides employees with fair rewards and benefits according to their contribution, a fair compensation culture motivates work performance, helps attract and retain competent employees, and serves as a core element of enhancing employment relationships (Namasivayam et al. [32]). As it can strongly promote employees' work engagement and job satisfaction, a fair compensation culture leads to a significant increase in hotel firms' employer attractiveness.

H3: Fair compensation culture has a positive effect on hotel firms' employer attractiveness.

A customer-focused culture is highly concerned with understanding customers' needs, wants, and expectations (Bartley et al. [33]: Fan and Ku [34]) and places the customer at the center of the organizational activities and operations (Fan and Ku [34]). In this culture, service employees develop a strong commitment to customer satisfaction and pursue high-quality service in a proactive manner to achieve long-term growth (Bartley et al. [33]; Fan and Ku [34]). As it enables organizations to perform the necessary behaviors to create superior value for customers, customer focus culture can realize continuous superior performance (Bartley et al. [33]). A customer-focused culture may generate a favorable service climate in which employees and customers work together to create higher service value, generating great satisfaction for both customers and employees (Chi and Gursoy [35]; Jeon and Choi [36]). The theory of emotional contagion suggests that interacting individuals experience transference and sharing of emotion, strongly supporting a positive relationship between employees and customer satisfaction. Service literature suggests that customers and employees in service encounters tend to automatically mimic and synchronize critical emotional cues, such as facial expressions, vocalizations, and postures, to converge emotionally. Furthermore, when customers are satisfied with employees, they actively engage in cooperative behavior to reciprocate employees' efforts, care about employees' well-being, and develop emotional bonds with employees Jeon and Choi [36]. Given the close relationship between customer satisfaction and employee satisfaction in service (Chi and Gursoy [35]; Jeon and Choi [36]), it is suggested that a customer-focused culture is closely related to employees' job satisfaction and enhances hotel firms' employer attractiveness.

H4: A customer-focused culture has a positive effect on hotel firms' employer attractiveness.

Innovation culture develops the norm of risk-taking by allowing freedom to try things and fail (O'Reilly [9]). It provides rewards for changes and creative ideas, while ensuring openness through active communication and knowledge sharing (O'Reilly [9]; Turnipseed and Turnipseed [37]; Chandler et al. [38]; and Li and Hsu [39]). Innovation culture is responsive to customer needs and emphasizes changes and improvements in high-quality products and services (Turnipseed and Turnipseed [37]). This enhances employees' perception that management supports them and develops reward systems to promote commitment to innovation (Chandler et al. [38]). In this culture, service employees explore new opportunities and ideas, perform formative investigations, and implement new ideas for better services (Li and Hsu [39]). In the process of transforming creative problem-solving ideas into applications, service employees not only advance their personal competences and abilities (Li and Hsu [39]), but also achieve high work performance and job satisfaction. Thus, it is predicted that innovation culture has a positive effect on hotel firms' employer attractiveness.

H5: Innovation culture has a positive effect on hotel firms' employer attractiveness.

4. Methodology

4.1. Data Collection. For an empirical analysis of the theoretical model, this study collected reviews of hotel firms by current and former employees on the Glassdoor website in the United States from January 2014 to December 2019. We collected review data from the Glassdoor website using Matlab's webread function. (According to Matlab's documentation, the webread function reads content from a website and returns the content in the form of data.) Moreover, anyone can sign up for Glassdoor and view the review data on-site. Therefore, data collection was difficult.

As one of the largest job search platforms (Corritore et al. [23]; Sull et al. [40]), Glassdoor has accumulated 55 million reviews since its launch in 2008 and has 67 million unique monthly visitors, covering approximately 900,000 organizations (Figure 1). After their identities are authenticated by Glassdoor, former and current employees write reviews anonymously without fear of reprisal by employers (Corritore et al. [23]), and firms cannot remove critical reviews. Users search for job post reviews in exchange for detailed site access (Corritore et al. [23]).

For the review of hotel employers, Glassdoor operates abrand- or firm-specific review site rather than individual hotel properties in the region. To identify hotel firms, we not only used a list of hotel chains in the United States provided by the website Looking for Booking but also used the search function in Glassdoor. In the search process, we used the terms "hotel(s)," "motel(s)," "lodge(ing)," "resort(s)," "vacation(s)," "casino(s)," "park(s)," and "hospitality." Based on these approaches, we initially collected 78,563 reviews from 189 hotel firms on Glassdoor, with at least 100 reviews in November 2020. As this study measures organizational culture at the corporate level by combining reviews, we must ensure sufficient reviews to estimate cultural attributes (Corritore et al. [23]). Thus, we set a restriction on the minimum number of five reviews per quarter. Regarding the frequency and distribution of reviews over time, some global hotel firms have a large volume of constant reviews, while others have a few sparse postings. After dropping the hotel firms without more than five reviews per quarter and excluding non-English reviews for the machine learning process, we obtained sample data including 54,040 reviews in 157 hotel firms for the statistical analysis of the hypotheses.

Employee reviews on the Glassdoor platform contain self-initiated and anonymous reports on employees' life experiences (Das Swain et al. [41]). The large-scale employee review data adopted in this research overcomes a variety of limitations in the traditional survey method, such as the restricted scalability of data, temporal granularity, response (or nonresponse) bias, and social desirability bias (Das Swain et al. [41]). The platform's review data encompass objective information, such as pay, work hours, and fringe benefits, and free-form textual data that inform various aspects of organizational experiences and attributes of organizational culture. The real-life languages used in the reviews reflect the shared experiences of employees without being framed by the theoretical terms of the academic researchers' survey questionnaires. The affordance of descriptive text in employee reviews provides researchers with an accessible and scalable medium for observing cultural differences and organizational characteristics (Das Swain et al. [41]).

4.2. Measurement. The independent variable of this research is the different attributes of organizational culture, and we developed language-based measures of cultural attributes by using LDA topic modeling (Blei [24]; Maier et al. [25]; Corritore et al. [23]). The topic modeling approach identifies the hidden structure of documents by generating interpretable topic distributions (Figure 1). LDA uses a mixed-membership model of grouped data, as each group exhibits multiple topics with different proportions. In the topic modeling process, LDA makes a "bag of words" assumption that discards word orders in documents (Blei [24]; Maier et al. [25]; Corritore et al. [23]). LDA inputs a document-term matrix, in which the rows have reviews and the columns have unigram counts. It identifies distinct topics across the corpus by collecting words that frequently co-occur in each review. LDA then outputs a document-topic

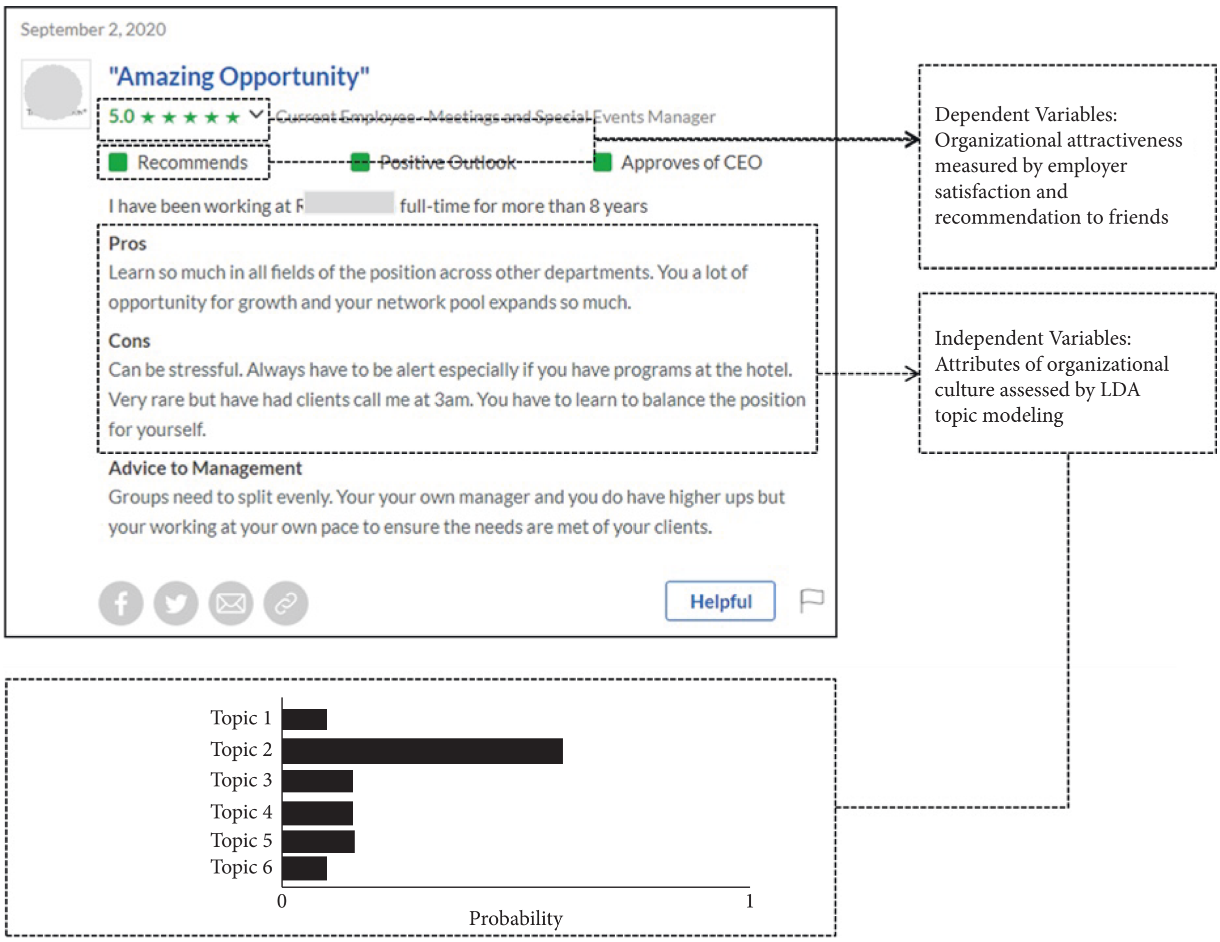


Figure 1: Example of employee review in Glassdoor and conceptualization of variables.

matrix that shows a probabilistic mixture of topics in each review document by providing percentages across all topics (Blei [24]; Maier et al. [25]; Corritore et al. [23]) (Figure 1 and Table 1).

To measure organizational culture through topic modeling of employee reviews in Glassdoor data, we integrated a firm's quarterly reviews (Figure 1), generated the probability of 100 cultural topics through unsupervised machine learning in LDA, matched relevant topics to different cultural attributes, and assessed their strength by combining the probability of relevant topics (Table 1). For more specific topic modeling processes, we followed the four-step approach proposed by Maier et al. [25]. The process consisted of (1) data cleaning and preprocessing, (2) choosing a number of topics, and (3) confirming topic interpretation and validity.

First, data cleaning and preprocessing include the standard procedures for processing unstructured text data, such as tokenization, discarding punctuation and capitalization of words, filtering out stop words, discarding both highly frequent and infrequent terms, and stemming and/or lemmatizing (Maier et al. [25]). We aggregated quarterly reviews of hotel firms and performed a basic cleaning of text documents to produce topics.

Second, in the application of the LDA machine learning function, choosing the number of topics is one of the most complicated tasks because no standard procedure exists that guides the setting of an appropriate number of topics. LDA allows users to set the number of topics freely (e.g., 30, 50, 100, and 500). Generating a small number of broad topics involves the problem of having general topics containing different themes; in contrast, accepting many topics generates highly specific and narrow topics (Maier et al. [25]). Thus, we decided to generate a relatively large number of topics (100) to obtain more precisely defined topics.

Third, topic interpretation and validity confirmation are the most important aspects of LDA modeling to effectively measure cultural attributes. Although LDA can generate multiple topics through an unsupervised learning process, it cannot present the semantics of obtained topics. The LDA model results are not deterministic and should be assessed against the background of substantive theoretical constructs (Maier et al. [25]). Thus, the most straightforward approach is to read individual topics and terms with the highest frequencies in a topic, review the meaning of the topics, and develop a label describing their substantive content (Maier et al. [25]; Corritore et al. [23]).

For the analysis of organizational culture, we adopted a bottom-up approach, in which we generated a relatively large number of 100 topics and performed the coding process. Unsupervised machine learning generated 100 topics from

Table 1: Construct measurement by topics generated by LDA.

Construct	Topic	Frequent Term
Collaborative culture	3	Friendly, environment, great, work, atmosphere, helpful, everyone, coworkers, team, worker, fun, sometimes, pleasant, relaxed, welcoming
	5	Work, love, great, amazing, people, really, intern, awesome, place, wish, enjoy, caring, hard, team, environment
	8	Make, everyone, help, feel, like, thing, way, every, willing, know, same, think, something, just, else
	9	Like, family, feel, stay, treat, part, friend, always just, well, number, come, definitely, enjoy, work
	14	Work, environment, place, great, really, positive, fun, team, enjoy, hard, professional, tough, exciting, supportive, chance
	16	Good, work, nice, people, far, coworker, bit, place, building, everything, load, area, definitely, heavy, generally
	22	Work, great, place, good, home, excellent, colleague, well, smart, think, social, clear, condition, tight, add
	47	Staff, friendly, management, short, always, work, sometimes, busy, good, shift, colleague, hour, environment, finish, fairmont
	51	Team, member, value, share, family, together, need, supportive, top, core, truly, well, part, wonderful, positive
	53	Environment, work, fun, great, good, fast, friendly, paced, challenge, supportive, colleague, overall. Beautiful, professional, win
	64	Work, really, love, people, back, enjoy, face, help, everyone, laid, everyday, interact, able, community, appreciate
Employee development culture	13	Opportunity, room, advancement, growth, benefit, plenty, small, little, offer, compensation, pto, competitive, position, discounted, fulltime
	23	Company, opportunity, move, grow, growth, lot, willing, advance, city, career, offer, great, quickly, limited, limited
	24	Opportunity, career, growth, growth, development, great, culture, learn, challenge, company, excellent, progression, leadership, path, compensation
	29	Company, associate, culture, care, grow, truly, hospitality, amp, leader, focus, industry, success, year, promotion, kimpton
	41	Training, program, opportunity, development, excellent, property, great, growth, promotion, company, process, promotion, career, white, engage
	45	Move, many, opportunity, position, department, different, transfer, around, location, lot, difficult, hard, advance, available, entry
	59	Company, many, culture, value, business, provide, grow, work life, lead, field, challenge, encourage, new, change, still
	61	Experience, learn, lot, skill, different, gain, knowledge, difficult, great, interaction, training, exposure, variety, new, type
	76	Expectation, management, support, training, high, well, set, goal, expect, due, little, need, pressure, issue, unrealistic
Fair compensation culture	11	Great, benefit, salary, travel, competitive, culture, amazing, package, company, rule, strict, awesome, minimal, corporate, advancement
	18	Hotel, discount, employee, room, rate, benefit, travel, perk, cafeteria, meal, advance, renovate, loyalty, paid, reduce
	20	Great, benefit, perk, awesome, location, atmosphere, sometimes, vary, strict, empower, diverse, staffed, throughout, starting, split
	26	Pay, low, good, salary, benefit, decent, compare, little, bonus, nice, workload, poor, lifestyle, odd, million
	34	Company, great, benefit, reward, well, fantastic, amazing, offer, perk, excellent, recognize, vision, especially, recognition, hotels
	42	Good, benefit, pay, union, fair, salary, plus, employee, appreciation, provide, non, teamwork, community, lower, quality
	44	Good, work, salary, environment, professional, training, standard, experience, benefit, personal, facility, great, less, worldwide, learning
	52	Great, benefit, lot, good, atmosphere, environment, fun, beautiful, culture, upward, mobility, move, movement, potential, consistent
	67	Pay, job, good, people, easy, decent, enough, suck, get, nice, sometimes, low, slow, amount, work
	79	Pay, wage, low, minimum, hourly, hour, overtime, increase, less, tip, living, fair, barely, rate, uniform
	81	Work, life, balance, personal, difficult, family, outside, compensation, environment, ring, listens, developer, staff, long, awareness, 5060
	96	Benefit, health, insurance, 401k, discount, medical, plan, vacation, offer, dental, pay, match, include, travel, etc.

Table 1: Continued.

Construct	Topic	Frequent Term
Customer focus culture	49	Customer, make, sure, decision, guest, feel, happy, inn, stay, take, appreciate, long, term, thing, resort, love
	69	Customer, guest, always, deal, sometimes, problem, make, happy, moment, time, job, never, keep, coworkers, create, fun
	92	Customer, customer, service, guest, experience, skill, learn, rude, quality, interact, good, kind, set, business, sometimes develop,
Innovation culture	28	Company, team, many, process, technology, big, change, talent, organization, global, leadership, focus, culture, large, spirit
	56	New, always, change, idea, come, need, way, start, person, something, right, year, bring, think, listen
	73	Management, hotel, department, allow, manager, create, team, keep, project, improve, site, revenue, director, senior, quality

quarterly reviews, and three researchers directly reviewed and selected relevant topics to match the cultural attributes of the hotel firms (Table 1). In the matching process, each researcher independently reviewed and selected relevant topics that matched theoretical concepts. Upon selecting independently coded topics, we followed the decision rule proposed by Corritore et al. [23] and selected topics in which at least two coders independently matched the cultural attributes. The decision process led to the selection of 40 topics. As Table 1 shows, the five attributes of organizational culture encompass multiple topics and key terms. Finally, we added the probabilities of the selected topics to measure the six attributes of organizational culture and added them to the analysis model as an independent variable.

The dependent variable of this research is the employer attractiveness of hotel firms, which we measure using two indicators in Glassdoor reviews. One measurement of attractiveness is "employer satisfaction," rated by employees on a 5-point scale (Figure 1); the other is the employee's answer to the question of whether the user "recommends the firm to friends" (Figure 1). Regarding this question, we input 1 for recommendation, 0 for neutral or nonanswer, and −1 for no recommendation. To make a corporate-level assessment, we calculated the means of all quarterly ratings presented by the employees.

The detailed process of creating independent and dependent variables for regression is summarized as follows:

Step 1. Create a list of famous hotels on Glassdoor

Step 2. Aggregate total reviews (sum of "pros" and "cons") of hotel firms and remove hotels with little or no review data.

Step 3. After basic cleaning of the total review text data, perform tokenization of the whole review text data.

Step 4. Vectorize the tokenization results using the bag-of-words model and fitting the LDA model to the vectorization results of the whole review data with 100 topics.

Step 5. Based on the fitted LDA model results, classify the 100 topic results into five cultural attributes using each topic's most frequent keywords.

Step 6. Calculate the topic probabilities for each review based on the fitted LDA model results.

Step 7. Define the score for five cultural attributes as a summation of the probability values for the topics belonging to each cultural attribute.

Step 8. Collect quarterly review data for each hotel and calculate the quarterly scores of five cultural attributes for each hotel as the average score for the five cultural attributes of the reviews in the quarter.

Step 9. Define the independent variables as the scores of the five cultural attributes for each quarterly and each hotel.

Step 10. For collected review data for each quarter and for each hotel, calculate average values of the "employer satisfaction" and "recommends the firm to friends" indicators in the reviews.

Step 11. Define the dependent variables as the average values of the two indicators for each quarterly and hotel.

The control variables of this research include the "logged number of total reviews" in a hotel firm, "logged number of quarterly reviews," and "classification of hotels." As the substantial difference in the number of reviews among hotel firms can cause systematic variations in cultural attribute measures (Corritore et al. [23]), we input both the logged number of total reviews and quarterly reviews to control for such potential influences. Finally, to control for hotel classification, we input 1 for the hotel brands classified as "luxury" and "upper upscale" hotels, while inputting 0 for all others. We expect that hotel firms with a large size and high service quality may offer better employment conditions than others, significantly affecting employer attractiveness.

Finally, although organizational culture reproduces itself in the socialization of new members and maintains high stability, disruptive organizational events such as new organizational leaders, mergers and acquisitions, and business crises can initiate sudden cultural changes and dynamisms (Schein [10]). This study calculated the Z-score to consider the unusual cultural changes in the statistical analysis (Cousineau and Chartier [42]) of all the probabilities of cultural attribute topics in each sample firm, to detect outliers. As an effective approach to identifying outliers, the *Z*-Score measures the distance of a data point from the mean using standard deviations. A positive value indicates that the

Table 2: **Descriptive statistics and correlations** ($n = 2,116$). *Note.* $^{*}p < 0.05$, $^{**}p < 0.01$.

	Means	S.D.	1	2	3	4	5	6	7	8	9
Log no. Total review	2.460	0.508									
Log no. Quarterly review	1.184	0.390	0.839**								
Classification	0.19	0.390	0.105**	0.067**							
Collaborative	0.107	0.026	−0.038	0.020	0.13**						
Employee development	0.077	0.025	0.057**	0.082**	0.072**	−0.045*					
Fair compensation	0.094	0.024	0.034	0.040	0.094**	−0.007	0.131*				
Customer focus	0.038	0.015	0.094**	0.086**	−0.053*	−0.073**	−0.077**	−0.216**			
Innovation	0.023	0.011	−0.035	−0.003	−0.070**	−0.073**	0.189**	−0.002	−0.037		
Employer satisfaction	3.367	0.578	0.195**	0.271**	0.214**	0.291**	0.278**	0.218**	−0.016	0.034	
Employer recommendation	0.163	0.344	0.197**	0.249**	0.165**	0.225**	0.292**	0.184**	0.002	0.018	0.832**

Table 3: **Results of regression analysis. *Note.*** $^{**}p < 0.01$, $^{***}p < 0.001$.

	Employer satisfaction		Employer recommendation	
	Path coefficient	T-statistic (p-value)	Path coefficient	T-statistic (p-value)
Log no. Total review	−0.072*	−2.103 (0.036)	−0.007	−0.206 (0.837)
Log no. Quarterly review	0.286***	8.326 (0.000)	0.212***	5.941 (0.000)
Classification	0.135***	7.106 (0.000)	0.091***	4.603 (0.000)
Collaborative	0.282***	14.911 (0.000)	0.225***	11.424 (0.000)
Employee development	0.239***	12.472 (0.000)	0.265***	13.326 (0.000)
Fair compensation	0.179***	9.322 (0.000)	0.146***	7.337 (0.000)
Customer focus	0.051**	2.667 (0.008)	0.057**	2.874 (0.004)
Innovation	0.020	1.029 (0.304)	−0.007	−0.332 (0.740)
F-value	102.222***		74.776***	
R^2	0.277		0.218	

observation is above the mean, whereas a negative value is below the mean. This study eliminated observations with a Z-score greater than 3 or less than −3, to consider the sudden cultural changes in the statistical analysis.

5. Analysis Result

The analysis results in Table 2 present the descriptive statistics and bivariate correlations of the variables for the analytical sample. Consistent with our expectations, four cultural attributes—collaborative, employee development, fair compensation, and customer focus—have a positive and significant correlation with employer satisfaction. Furthermore, four cultural attributes are positively and significantly correlated with employer recommendations, but innovation culture has no significant correlation. Finally, control variables such as the logged number of total reviews, number of quarterly reviews, and classification have a positive and significant correlation with the dependent variables.

To analyze the influence of organizational culture on employer attractiveness, we performed a linear regression analysis using SPSS Version 25. Table 3 reports our main findings. On the one hand, the statistics support many of our predictions and show that the four cultural attributes of collaborative culture ($\beta = 0.282$, $p < 0.001$), employee development culture ($\beta = 0.239$, $p < 0.001$), fair compensation culture ($\beta = 0.179$, $p < 0.001$), and customer focus culture ($\beta = 0.051$, $p < 0.01$) have a positive and significant impact on employer satisfaction ($R^2 = 0.277$). However, contrary to our expectations, innovation culture has no significant effect on employer satisfaction. On the other hand, the results show same result that that the four cultural attributes of collaborative culture ($\beta = 0.225$, $p < 0.001$), employee development culture ($\beta = 0.265$, $p < 0.001$), fair compensation culture ($\beta = 0.146$, $p < 0.001$), and customer focus culture ($\beta = 0.057$, $p < 0.01$) have a positive and significant impact on employer satisfaction ($R^2 = 0.218$). Furthermore, the findings show that innovation culture has no significant effect on employer recommendations.

Regarding the influence of control variables, both the number of quarterly reviews and classifications of hotels consistently and positively affect employer attractiveness, suggesting that the conditions of firm size, service quality, and brand reputation cause variations in the research model and employer attractiveness. In summary, the statistical analysis suggests that four cultural attributes—collaborative culture, employee development culture, fair compensation culture, and customer focus culture—enhance hotel firms' employer attractiveness, but innovation culture in hotels is not significantly related to employer attractiveness to employees.

6. Discussion and Conclusion

6.1. Theoretical Implications. Although organizational culture is deeply related to diverse organizational outcomes, existing hospitality studies have a relatively narrow focus on employee and organizational performance. To address this limitation, this study focuses on the employer attractiveness of hotel firms as a critical outcome of organizational culture.

This study contributes to the literature by exploring the relationship between organizational culture and employer attractiveness. As hotels have chronic problems of high turnover rate and shortage of skilled labor, a hotel's attractiveness as an employer is critical to gaining competitive advantage in the labor market. This research highlights the importance of favorable cultural attributes, showing the positive effects of four cultural attributes: collaborative culture, employee development culture, fair compensation culture, and customer-focus culture. Organizational culture clarifies the benefits, uniqueness, and distinctiveness of a hotel against its competitors (Gehrels and de Looij [3]; Leekha Chhabra and Sharma [4]; and Theurer et al. [5]). This study shows that a favorable organizational culture in a hotel is an important factor for current and prospective employees in making employment decisions. It also helps hotels acquire and retain talent.

This study adopted a novel approach for operationalizing cultural attributes. Large-scale review data produced by current and former employees and combined machine learning and researchers' theoretical reasoning were used to confirm the validity of the construct measurements. The measurement process included aggregating reviews at the hotel firm level, extracting cultural topics through LDA, and calculating the probability of cultural attributes by combining topics in accordance with the theoretical definition. This new methodological approach enables researchers to overcome the limitations of self-reporting surveys. Although the classic survey methodology is less expensive and time-consuming, it cannot access "deeper" cultural attributes that are represented in the form of symbolic meanings, semiotics, and fundamental assumptions prevalent among employees (Denison et al. [26]). Traditional surveys measure cultural attributes using general theoretical terms and words presented in the organizational culture theory. Employee reviews on Glassdoor, however, enable researchers to gain direct access to the language and expressions that hotel employees use in their workplace. Researchers can identify organizational culture directly by observing the language and terms in which employees describe the organization to outsiders, as this reveals their underlying beliefs and assumptions (Corritore et al. [23]).

Moreover, the aggregation of review data enables the assessment of cultural attributes at the corporate level, along with a comparative analysis across organizations, which is a step ahead of the traditional self-reporting survey at an individual level. Analyzing the influence of specific cultural attributes on individual outcomes, the traditional survey method focuses on evaluating the perceptions of a few individuals in an organization that are psychologically meaningful and impressive to them (He et al. [21]; Denison et al. [26]). However, surveys of a few employees in a firm can be biased and inaccurate in terms of representing the firm's organizational culture as a whole (Denison et al. [26]). For a more accurate analysis of organizational culture, meaningful data are attainable when researchers collect personal data under the same set of cultural concepts and aggregate them at the organizational level, which allows for comparison across organizations (Denison et al. [26]). The aggregation of employee reviews in a hotel firm constitutes a more valid instrument for the study of organizational culture, as it enables researchers to measure cultural attributes at the corporate level with minimal personal bias. The large-scale data in this study ensured a higher validity of the construct measurement and enhanced the generality of the analysis results.

Finally, this study proposed a new text-mining structure for analyzing organizational culture, based on large-scale employee review data, and demonstrated its applicability and usability. The new approach in this research presented a ten-step procedure to perform data collection, tokenization of text, application of the LDA model to measure organizational culture, manual coding of cultural attributes, construction of quarterly data for regression analysis, and testing of the research model. Given the systematic analysis process and the sound statistical results supporting the hypotheses, this study's new text-mining structure can effectively guide researchers who adopt large-scale text data and topic modeling tools, to perform organizational culture and behavior studies.

6.2. Practical Implications. Hotel firms have highly labor-intensive services, and good service delivery is largely dependent on the motivation, capabilities, and attitudes of employees. Acquiring talented and capable employees is one of the most critical elements in the hospitality industry because of the chronic problem of high turnover in the United States (Dusek et al. [1]; Park and Min [2]). Improving the employer attractiveness of hotels involves a variety of positive outcomes for employees and hotels. Desirable and satisfactory employers can induce good organizational commitment and job performance among employees, as well as create good service quality and customer satisfaction (Chi and Gursoy [35]), while decreasing their absenteeism and turnover intentions (Yang [43]). Employer attractiveness reduces the cost of employee acquisition, improves employee loyalty, and ensures employee retention, all of which create solid corporate branding and competitive advantage (Leekha Chhabra and Sharma [4]).

The results of this study provide critical insights for leaders and human resource (HR) managers in attracting talent. The analysis results advise leaders to promote favorable cultural attributes such as collaboration, employee development, fair compensation, and customer focus culture to strengthen the hotel's attractiveness as an employer. In particular, as HR systems are deeply associated with the shaping of organizational culture (Lengnick-Hall et al. [44]; Chow [45]), managers should design systematic HR practices to foster employee career advancement and capability growth while offering fair compensation to promote employer brands to current and prospective employees.

6.3. Limitations and Future Research. Although this study contributes to the hospitality literature by analyzing the relationship between organizational culture and employer attractiveness, it has limitations that should be addressed in future research. On the one hand, the current research analyzed organizational culture at the hotel firm level, but individual hotel properties may develop diverging cultural attributes, even if they belong to the same franchise or chain systems. Thus, future research may address this limitation by analyzing the influence of property-level attributes on employer attractiveness and performance. On the other hand, the empirical analysis in this research focused only on hotel firms in the United States using Glassdoor reviews written in English. Thus, the validity of our research results is limited to English-speaking users of Glassdoor in the United States. When we consider that national culture may affect the organizational culture of firms, future research can investigate the influence of organizational culture on employer attractiveness in different national and cultural contexts by using reviews in different languages to enhance the external validity of our results. Despite these restrictions, new attempts in this study, such as the exploration of new relationships between constructs, the novel operationalization of organizational culture, and a methodology based on machine learning processes, provide crucial insights for future research in hospitality studies.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors have declared that no competing interests exist.

Acknowledgments

The research of S.-Y. Choi work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (Grant no. 2021R1F1A1046138).

References

[1] G. A. Dusek, C. P. Ruppel, Y. Yurova, and R. Clarke, "The role of employee service orientation in turnover in the us hotel industry," *Journal of Organizational Culture, Communications and Conflict*, vol. 18, no. 2, p. 87, 2014.

[2] J. Park and H. (K. Min, "Turnover intention in the hospitality industry: a meta-analysis," *International Journal of Hospitality Management*, vol. 90, Article ID 102599, 2020.

[3] S. A. Gehrels and J. de Looij, "Employer branding: a new approach for the hospitality industry," *Research in Hospitality Management*, vol. 1, no. 1, pp. 43–52, 2011.

[4] N. Leekha Chhabra and S. Sharma, "Employer branding: strategy for improving employer attractiveness," *International Journal of Organizational Analysis*, vol. 22, no. 1, pp. 48–60, 2014.

[5] C. P. Theurer, A. Tumasjan, I. M. Welpe, and F. Lievens, "Employer branding: a brand equity-based literature review and research agenda," *International Journal of Management Reviews*, vol. 20, no. 1, pp. 155–179, 2018.

[6] J. E. Sheridan, "Organizational culture and employee retention," *Academy of Management Journal*, vol. 35, no. 5, pp. 1036–1056, 1992.

[7] F. Lievens and H. Scott, "The relation of instrumental and symbolic attributes to a company's attractiveness as an employer," *Personnel Psychology*, vol. 56, no. 1, pp. 75–102, 2003.

[8] J. B. Barney, "Organizational culture: can it be a source of sustained competitive advantage?" *Academy of Management Review*, vol. 11, no. 3, pp. 656–665, 1986.

[9] C. O'Reilly, "Corporations, culture, and commitment: motivation and social control in organizations," *California Management Review*, vol. 31, no. 4, pp. 9–25, 1989.

[10] E. H. Schein, "Organizational culture," *American Psychological Association*, vol. 45, 1990.

[11] B. Schneider, W. H. Macey, W. C. Lee, and S. A. Young, "Organizational service climate drivers of the American customer satisfaction index (acsi) and financial and market performance," *Journal of Service Research*, vol. 12, no. 1, pp. 3–14, 2009.

[12] Y. Li and S. H. Songshan, "Hospitality service climate, employee service orientation, career aspiration and performance: a moderated mediation model," *International Journal of Hospitality Management*, vol. 67, no. 24–32, pp. 24–32, 2017.

[13] J. A. K. Hee and J. A. Busser, "Impact of service climate and psychological capital on employee engagement: the role of organizational hierarchy," *International Journal of Hospitality Management*, vol. 75, no. 1–9, pp. 1–9, 2018.

[14] V. Bellou and I. A. Andreas, "Examining organizational climate in Greek hotels from a service quality perspective," *International Journal of Contemporary Hospitality Management*, vol. 21, 2009.

[15] M. Dawson, J. Abbott, and S. Shoemaker, "The hospitality culture scale: a measure organizational culture and personal attributes," *International Journal of Hospitality Management*, vol. 30, no. 2, pp. 290–300, 2011.

[16] A. Bavik, "Developing a new hospitality industry organizational culture scale," *International Journal of Hospitality Management*, vol. 58, pp. 44–55, 2016.

[17] A. Datta and R. Singh, "Determining the dimensions of organizational climate perceived by the hotel employees," *Journal of Hospitality and Tourism Management*, vol. 36, pp. 40–48, 2018.

[18] M. Tepeci and A. L. B. Bartlett, "The hospitality industry culture profile: a measure of individual values, organizational culture, and person–organization fit as predictors of job satisfaction and behavioral intentions," *International Journal of Hospitality Management*, vol. 21, no. 2, pp. 151–170, 2002.

[19] J.-Te Yang, "Knowledge sharing: investigating appropriate leadership roles and collaborative culture," *Tourism Management*, vol. 28, no. 2, pp. 530–543, 2007.

[20] J. A. K. Hee, J. Busser, and H.-M. Choi, "Service climate: how does it affect turnover intention?" *International Journal of Contemporary Hospitality Management*, vol. 30, no. 1, pp. 76–94, 2018.

[21] Y. He, W. Li, and K. Keung Lai, "Service climate, employee commitment and customer satisfaction," *International Journal of Contemporary Hospitality Management*, vol. 23, no. 5, pp. 592–607, 2011.

[22] R.-S. María del Rosario, S.-M. Patricia S, and R. Díaz-Pichardo, "Eco-innovation and organizational culture in the hotel industry," *International Journal of Hospitality Management*, vol. 65, pp. 71–80, 2017.

[23] M. Corritore, A. Goldberg, and S. B. Srivastava, "Duality in diversity: how intrapersonal and interpersonal cultural heterogeneity relate to firm performance," *Administrative Science Quarterly*, vol. 65, no. 2, pp. 359–394, 2020.

[24] D. M. Blei, "Probabilistic topic models," *Communications of the ACM*, vol. 55, no. 4, pp. 77–84, 2012.
[25] D. Maier, A. Waldherr, P. Miltner et al., "Applying LDA topic modeling in communication research: toward a valid and reliable methodology," *Communication Methods and Measures*, vol. 12, no. 2-3, pp. 93–118, 2018.
[26] D. Denison, L. Nieminen, and L. Kotrba, "Diagnosing organizational cultures: a conceptual and empirical review of culture effectiveness surveys," *European Journal of Work & Organizational Psychology*, vol. 23, no. 1, pp. 145–161, 2014.
[27] C. Glisson, "Assessing and changing organizational culture and climate for effective services," *Research on Social Work Practice*, vol. 17, no. 6, pp. 736–747, 2007.
[28] M. A. Gillespie, D. R. Denison, S. Haaland, R. Smerek, and W. S. Neale, "Linking organizational culture and customer satisfaction: results from two companies in different industries," *European Journal of Work & Organizational Psychology*, vol. 17, no. 1, pp. 112–132, 2008.
[29] S. Karl-Erik and R. Simons, "Collaborative climate and effectiveness of knowledge work–an empirical study," *Journal of Knowledge Management*, vol. 6, no. 5, pp. 420–433, 2002.
[30] C. H. Lee and N. T. Bruvold, "Creating value for employees: investment in employee development," *International Journal of Human Resource Management*, vol. 14, no. 6, pp. 981–1000, 2003.
[31] B. Kuvaas and A. Dysvik, "Perceived investment in employee development, intrinsic motivation and work performance," *Human Resource Management Journal*, vol. 19, no. 3, pp. 217–236, 2009.
[32] K. Namasivayam, Li Miao, and X. Zhao, "An investigation of the relationships between compensation practices and firm performance in the us hotel industry," *International Journal of Hospitality Management*, vol. 26, no. 3, pp. 574–587, 2007.
[33] B. Bartley, S. Gomibuchi, and R. Mann, "Best practices in achieving a customer-focused culture," *Benchmarking: An International Journal*, vol. 14, no. 4, pp. 482–496, 2007.
[34] Yi-W. Fan and E. Ku, "Customer focus, service process fit and customer relationship management profitability: the effect of knowledge sharing," *Service Industries Journal*, vol. 30, no. 2, pp. 203–223, 2010.
[35] C. G. Chi and D. Gursoy, "Employee satisfaction, customer satisfaction, and financial performance: an empirical examination," *International Journal of Hospitality Management*, vol. 28, no. 2, pp. 245–253, 2009.
[36] H. Jeon and B. Choi, "The relationship between employee satisfaction and customer satisfaction," *Journal of Services Marketing*, vol. 26, no. 5, pp. 332–341, 2012.
[37] P. H. Turnipseed and D. L. Turnipseed, "Testing the proposed linkage between organizational citizenship behaviours and an innovative organizational climate," *Creativity and Innovation Management*, vol. 22, no. 2, pp. 209–216, 2013.
[38] G. N. Chandler, C. Keller, and D. W. Lyon, "Unraveling the determinants and consequences of an innovation-supportive organizational culture," *Entrepreneurship: Theory and Practice*, vol. 25, no. 1, pp. 59–76, 2000.
[39] M. Li and C. H. C. Hsu, "A review of employee innovative behavior in services," *International Journal of Contemporary Hospitality Management*, vol. 28, no. 12, pp. 2820–2841, 2016.
[40] D. Sull, C. Sull, and A. Chamberlain, *Measuring culture in leading companies*, Introducing the MIT SMR/Glassdoor Culture 500, MIT Sloan Management Review, 2019.
[41] V. Das Swain, K. Saha, M. D. Reddy, H. Rajvanshy, G. D. Abowd, and M. De Choudhury, "Modeling organizational culture with workplace experiences shared on Glassdoor," in *Proceedings of the 2020 CHI conference on human factors in computing systems*, Honolulu, HI, USA, April 2020.
[42] D. Cousineau and S. Chartier, "Outliers detection and treatment: a review," *International Journal of Psychological Research*, vol. 3, no. 1, pp. 58–67, 2010.
[43] J.-Te Yang, "Antecedents and consequences of job satisfaction in the hotel industry," *International Journal of Hospitality Management*, vol. 29, no. 4, pp. 609–619, 2010.
[44] M. L. Lengnick-Hall, C. A. Lengnick-Hall, L. S. Andrade, and B. Drake, "Strategic human resource management: the evolution of the field," *Human Resource Management Review*, vol. 19, no. 2, pp. 64–85, 2009.
[45] I. H.-S. Chow, "The roles of implementation and organizational culture in the HR-performance link," *International Journal of Human Resource Management*, vol. 23, no. 15, pp. 3114–3132, 2012.

Hindawi
Complexity
Volume 2022, Article ID 6102963, 11 pages
https://doi.org/10.1155/2022/6102963

Research Article

Stackelberg Game Perspective on Pricing Decision of a Dual-Channel Supply Chain with Live Broadcast Sales

Rong Zhang,[1] Xiaoying Zhang,[2] and Bin Liu [3]

[1]*Research Center of Logistics, Shanghai Maritime University, Shanghai 201306, Pudong, China*
[2]*School of Economics and Management, Shanghai Maritime University, Shanghai 201306, Pudong, China*
[3]*Business School, University of Shanghai for Science and Technology, Shanghai 200093, Yangpu, China*

Correspondence should be addressed to Bin Liu; liubhnau@163.com

Received 25 January 2022; Accepted 29 March 2022; Published 16 April 2022

Academic Editor: Ning (Chris) Chen

Focusing on the dual-channel supply chain with live broadcasts selling, this paper investigates the service overflow of live broadcasts with Stackelberg game perspective and the impact of retailers' different market potentials on the pricing decisions of dual-channel members. Meanwhile, it also evaluates the pricing strategy of online retailers after introducing KOL (Key Opinion Leader) live broadcasts. The results show that when one of the dual-channel retailers adopts live broadcast sales, the live broadcast service overflow will have an adverse impact on it, but the degree of the impact depends on the market potential of supply chain members, and different power structures can be used to offset the adverse impact of live broadcast service overflow. Then, the live broadcast sales service overflow will have a certain beneficial impact on online retailers under certain circumstances. Furthermore, with the increase of live broadcast sales service overflow, the retail prices of both companies will decline, while the live broadcast sales service overflow is more beneficial for consumers.

1. Introduction

In recent years, with the widespread popularity of mobile networks and smartphones in China, live broadcasting has developed rapidly as a new mode of communication and gradually became a new way of people's social life. According to the "44th Statistical Report on Internet Development in China" released by the China Internet Network Information Center (2019), as of June 2019, the number of users watching live webcasts in China has reached 433 million, more than half of the total number of Internet users. Affected by COVID-19 in early 2020, people's offline life, such as consumption and education, has stagnated. The live broadcast once again uses its characteristics to penetrate people's lives in an all-around way, such as e-commerce live broadcast, classroom live broadcast, live broadcast of epidemic prevention, and so on.

In 2016, e-commerce live broadcasts developed rapidly as a new sales model. E-commerce platforms gradually began to discover the profitability of live broadcasts and adopted a new model of "live broadcast + e-commerce," which simply operated shopping pages and live broadcast pages to link each other. As a new business model, the live broadcast has changed the way of communication between merchants and consumers. For example, small businesses and individual sellers can publicize and display their products through live broadcasting. Live demonstrations of products provide richer information and a more interactive experience than the text descriptions and pictures on the web because live communication can not only show the appearance and functions of the product, but also demonstrate the use method and postuse effect of the product and even answer the questions of consumers during the live broadcast. These functions of live broadcasts greatly reduce consumers' uncertainty about products because consumers can easily understand products (such as clothing) and infer whether goods meet their preferences. Therefore, the live broadcast has gradually developed into a new sales method, and many retailers have adopted live broadcast sales to display and introduce their products. Since the service effect of live broadcast sales is affected by many factors, such as consumers' personal factors, the interaction with consumers in the live broadcast room will affect consumers' emotions, thereby affecting consumers' information screening and purchasing decisions. At the same time, the anchor's professionalism and the content of the live broadcast room affect the service effect of live broadcast sales. So, service overflow may occur, especially in dual-channel supply chains, when two channels provide different services in real life, one of the channels provides corresponding services in live broadcast sales, and services are provided between these two channels. The phenomenon of overflow has become more and more prominent, aggravating the conflict between the two channels and having a certain impact on the pricing of supply chain members and channel coordination issues.

This article uses mathematical modeling and numerical example simulation methods to establish a model to study when a retailer in a dual-channel supply chain uses live broadcast to sell and to discuss how the service overflow provided by live broadcast affects other members of the dual-channel supply chain and considers the two retailers' different market potentials. At the same time, the impact of live broadcast service overflow on pricing under different market potentials of two retailers is studied, and the optimal decision-making under different power structures is compared, and the retailer's profits are affected by live broadcast service overflow and market potential.

The literature involved in the research questions in the article is mainly divided into three categories: one is live sales. Reference [1] has integrated computer science, marketing, and other domain knowledge to study live broadcasts. They believe that social e-commerce is an Internet-based business application. Social interaction is a new social media that communicates with users to help consumers make decisions and obtain products and services on online channels. In order to study how live broadcast services affect user stickiness through user attachment, [2] developed a theoretical model based on social technology methods and attachment theory and found that both technical and social factors would increase user stickiness. Reference [3] thought that live shopping is a new social media model with high human-computer interaction (HCI). In the context of live sales in China, [4] studied the impact of celebrity product endorsement matching degrees on consumers' purchasing attitudes and developed a comprehensive model of online celebrity endorsements. Based on the perspective of social presence, according to the characteristics of e-commerce live broadcasting, Zhou et al. [5] combined SOR (Stimulus-Organism-Response) theory and TAM (Technology Acceptance Model) to depict the consumers' purchase intention in e-commerce live broadcasting and investigated the social presence factors affecting consumers' purchase intention, which is of great significance to the development of e-commerce live broadcasting market. Regarding live broadcast sales, from the perspective of customer loyalty, Chen [6] found that e-commerce live broadcast sales should focus on traffic, scenes, and content, as well as cultivating consumer trust and loyalty.

On dual-channel supply chain competition, [7], respectively, constructed the Stackelberg game model and Bertrand game model of the optimal price in the dual-channel supply chain to study the income distribution of members in the supply chain and proposed coordination strategies under different game models. Reference [8] studied the role of retail service levels in the dual-channel competitive market, and the results showed that improved retail services can effectively alleviate the competition and conflicts in the dual-channel. Reference [9] establishes the Stackelberg game and Bertrand game model to analyze the equilibrium strategy of manufacturers in the leading position in the dual-channel supply chain and further discussed the equilibrium prices and optimal returns of the supply chain participants. Reference [10] focused on the strategy of manufacturers to conduct dual-channel competition through direct sales channels and physical retail sales. They conducted a series of experiments to verify the model. The study found that the demand of the channel depends on the level of service provided by the channel, consumer product satisfaction, and shopping experience. Reference [11] investigated the competition of product types in a dual-channel supply chain composed of traditional retailers and online retailers. The results showed that online channels face more competition than traditional retailers when selling mainstream products in dual-channel competition. Reference [12] considered a dual-channel supply chain network composed of multiple competing manufacturers, multiple competing retailers, and multiple demand markets and established a dual-channel supply chain network equilibrium model to analyze the impact of three key factors on equilibrium and profits. Reference [13] studied the important role of channel coordination in the multichannel supply chain and provided manufacturers with a competitive advantage in opening online channels, deriving the best market strategies for multichannel manufacturers and retailers. Reference [14] established a model based on the theory of consumer utility to study dual channels, considering the ratio of free-riding consumers and the cost of consumer transfer, and compared the optimal pricing strategy and profit under decentralized decision-making. The study found out that the free-riding ratio and transfer cost have an important influence on the market game behavior of manufacturers and retailers. Chen et al. (2010) considered the service differences between channels and price factors, established a dual-channel competition model to evaluate the influence of channel service differences and the acceptance of network channels on dual channels, and compared the service levels and profits of different channels. The discovery of service competition made the dual-channel supply chain better than the single-channel one.

In the service spillover, [15] analyzed the optimal price of the entire dual-channel supply chain and the balanced competition among members of the dual-channel structure when there is free-riding behavior and the sharing of benefits. The results showed that revenue-sharing contracts could completely coordinate and disperse the entire dual-channel supply chain system. Revenue-sharing contracts and fixed price difference policies can coordinate and integrate dual-channel supply chains, while revenue-sharing contracts cannot fully coordinate and integrate the entire dual-channel supply chain. Reference [16] investigated the degree of influence of the free-riding effect on the channel selection of manufacturers and analyzed the changes in sales, equilibrium pricing, and profits of manufacturers in different channels under the influence of the free-riding effect.

Through the literature review of live broadcast sales and dual-channel supply chain [17], it can be seen that the existing research on live broadcast sales is only from a partial perspective, and most of the existing literature only studies the phenomenon, flow, and development trend of live broadcast sales. From a theoretical point of view, the existing literature rarely uses quantitative models to analyze live broadcast sales. In order to better discover the impact of live broadcast service spillovers on dual channels, the model sets the cross-price elasticity in dual channels to 1, which is computationally more efficient, including convenience, and highlights the influence of the live broadcast service retention coefficient on dual channels; from a practical point of view, the model calculation results show that the service effect of the live broadcast room not only directly affects the live broadcast sales channel, but also affects the online sales channel. The model calculation results provide feasible suggestions on how retailers in the dual-channel supply chain can make full use of live broadcasting as a sales method.

The rest of this article is organized as follows. Section 2 is the research hypothesis and basic model, and Section 3 is the Stackelberg game and the Nash game research on the model. Then, Section 4 analyzes the comparison of different pricing decisions and returns. Section 5 introduces the KOL live broadcast sales model for extended analysis. Finally, we conclude the results and suggest topics for future research in Section 6.

2. The Basic Model

This article focuses on a dual-channel supply chain consisting of a live-streaming retailer and an online retailer. All retailers will sell products purchased from the same wholesaler to final consumers, and live-streaming retailer is committed to displaying products to consumers through live broadcasts. During live sales, the retailer provided demand enhancement services, including communication with customers, presale advice, product display, advertising, and promotion. Undoubtedly, this kind of service increases the potential market demand because consumers can learn about products in the living and decide whether to buy products from the same store or another online retailer. Therefore, the effort spent by the live broadcast retailer may increase the potential market demand for itself and another online retailer, but the cost of live service will be paid by the retailer that conducts live broadcast sales.

This article analyzes two scenarios, one is that the live-streaming retailer determines the price before the online retailer, that is, the live-streaming retailer as Stackelberg game leader (Scenarios LS), and the other is that the online retailer determines the price before the live broadcast retailer (Scenarios OS). Assuming that the manufacturer is non-strategic, the retailer purchases goods at the wholesale price determined by the market. Both retailers subsequently added their respective profits to the wholesale price to determine the selling price of the goods. Because retailers are strategic companies, the final retail prices they charge are not the same; p_l and p_e are the prices of the live-streaming retailer and the online retailer's merchandise, respectively. The services provided by the live broadcast retailer during the live broadcast will help the live broadcast retailer and the online retailer to increase the demand. The needs of the live broadcast retailer are as follows:

$$D_l(p_l, s) = a_l - p_l + p_e + \gamma\sqrt{s}, \tag{1}$$

where a_l is the potential market demand of the live-streaming retailer, and the parameter s is the service provided by the live-streaming retailer to sell products to customers; s is a sales work carried out to show customers product features or answer customer questions related to the product, which may help increase sales. It is equivalent to the effort made by a live-streaming retailer, assuming that the increase in potential demand is diminishing returns to scale. The square root function used above is a concave function, which can depict the diminishing proportional returns. $\gamma\sqrt{s}$ is the part of the increase in demand for the service reservation of live broadcast retailer, which defines the reserved part of the sales activities of the live broadcast retailer; $(1-\gamma)\sqrt{s}$ is the part of the live broadcast sales service overflowing to the demand growth of online retailer, and $0 \leq \gamma \leq 1$. Therefore, the demand for online retailers is as follows:

$$D_e(p_e) = a_e - p_e + p_l + (1-\gamma)\sqrt{s}, \tag{2}$$

where parameter a_e is the potential market demand of online retailers, assuming that the cross-price elasticity of the two retailers is 1. The model assumes that the two retail channels facing consumers are symmetrical in all aspects, except that one is live sales, and the other is online sales. Therefore, it can be considered that consumers have a tendency to price products. Reference [18] applied similar demand function to investigate pricing decision of the "showrooming" in multichannel retail system.

The live broadcast retailer will pay a certain cost to sell the products to consumers. This can be in the form of recruiting live broadcasters, who show consumers information about the product. This cost of work only occurred by the live-streaming retailer, and the cost is proportional to the amount of work invested. Therefore, the profit function of the live broadcast retailer is as follows:

$$\pi_l(p_l, s) = D_l(p_l, s)(p_l - w) - s. \tag{3}$$

Similarly, the profit function of an online retailer is

$$\pi_e(p_e) = D_e(p_e)(p_e - w). \tag{4}$$

To facilitate the distinction in the subsequent calculation and analysis process, the subscripts l and e are used to represent the decision-making models led by live-streaming retailers and online retailers, respectively, and the superscript "$*$" represents the optimal result.

3. Model Analysis

This article is based on the analysis of the different leadership positions of the two retailers in determining the prices. The framework of the model is the Stackelberg games and the Nash game. The Stackelberg leadership game is a strategic game in which the leader company acts first, and then the follower company makes the best response. The leader envisions the best response of the follower and determines the best action on this basis. References [19, 20] applied the Stackelberg model in a multichannel retail environment. In the model of this article, this leadership is the power to set prices first and get other retailers to respond.

3.1. Scenarios LS: Live-Streaming Retailers as Stackelberg Leader. First, we suppose that the live-streaming retailer will determine the price before the online retailer. At this time, the live-streaming retailer will play a leading role in the pricing role. Both retailers have determined the best response price based on given wholesale price w and the retail prices of the other retailer. As this article assumes that both parties know all the information, in the game, the retailer will respond to the right price of the other retailer. The live broadcast retailer responds by setting the price and the service level of the live broadcast anchor, and the online retailer needs to set the price. To set the price, each retailer must maximize its own profits. The retail price charged by each retailer will be the sum of the retailer's profit and the wholesale price. Therefore, the corresponding price will be set according to the profit and the wholesale price. $p_l = w + m_l$ and $p_e = w + m_e$ are available. The retailer sets its own profit so that the sum of the wholesale price and the corresponding profit is the optimal retail price. For given w, m_l, and s, by maximizing the profit function of the online retailer, the optimal m_e of the online retailer can be obtained. By integrating the online retailer's optimal pricing into its own profit function, the live-streaming retailer sets its optimal response by maximizing its profit function. Maximize the profit function of the live broadcast retailer and get the best m_l and s of the live broadcast retailer. Therefore, the optimal responses p_l, p_e, and s are obtained.

The Stackelberg equilibrium for the live broadcast retailer to determine the price before the online retailer is

$$\begin{aligned}\max \pi_l(m_l, s) &= \left(a_l - (w + m_l) + (w + m_e) + \gamma\sqrt{s}\right)m_l - s,\\ \max \pi_e(m_e) &= \left(a_e - (w + m_e) + (w + m_l) + (1-\gamma)\sqrt{s}\right)m_e.\end{aligned} \tag{5}$$

Lemma 1. *Under Scenarios LS, the optimal p_l, p_e, and s can be obtained by the above formula,*

$$\begin{aligned} p_{lL}^{*} &= \frac{8\alpha_l + 4\alpha_e}{8 - (1+\gamma)^2},\\ p_{eL}^{*} &= \frac{\left(5-\gamma^2\right)\alpha_l + \left(6-\gamma-\gamma^2\right)\alpha_e}{8-(1+\gamma)^2},\\ s_L^{*} &= \left(\frac{(1+\gamma)\left(2\alpha_l + \alpha_e\right)}{8-(1+\gamma)^2}\right)^2. \end{aligned} \tag{6}$$

Based on Lemma 1, we can get Proposition 1.

Proof: To see the appendix. □

Proposition 1. *Under the decision of the live broadcast retailer as the leader, $\partial p_{lL}^*/\partial\gamma > 0$ and $\partial p_{eL}^*/\partial\gamma > 0$. This means the higher the service level retention coefficient, the higher the retailer's dual-channel sales price. When $a_l/a_e \geq \gamma^2 - 10\gamma - 3/6 - 2\gamma^2 + 20\gamma$, $\partial p_{lL}^*/\partial\gamma \geq \partial p_{eL}^*/\partial\gamma$, the level of live broadcast services has a greater impact on the prices of live sales channels than on online channels; otherwise, the opposite is true.*

Proof: to see the appendix.

Proposition 1 shows that the improvement of live broadcast services level by live broadcast retailers will increase the cost of live broadcast channels. However, with live broadcast retailers as the leader, members of the supply chain make independent decisions. Under the situation of greater market potential for live-streaming retailers, they may raise prices on a certain basis to obtain higher profits after learning that online retailer may raise prices. Moreover, when live broadcast service overflow rarely occurs, it means that most of the consumers attracted by retailers to provide live broadcast services purchase goods through live broadcast sales channels. Therefore, with the increase in the reserved portion of live broadcast services, retailers increased live broadcast service costs that are more borne by consumers of live broadcast channel channels, and the price of live broadcast sales channels has increased even more. In the case of low service retention coefficient, when online retailer occupies a higher market potential, they will set higher prices and occupy a higher market demand share. In this case, online retailer already has a high market potential, and the overflow of live broadcast services has played a positive role in the sales of online retailer. Therefore, with higher market potential the online retailer will benefit more from the overflow of live broadcast services. □

Proposition 2. *Under the decision of the live broadcast retailer as the leader, the demand for online channels and live broadcast channels can be derived, and the partial derivation of the demand with respect to the service retention coefficient can be $\partial D_{eL}^*/\partial\gamma > 0$ and $\partial D_{eL}^*/\partial\gamma > 0$; as γ increases, the demand for both channels will increase accordingly. When $a_l/a_e \geq \gamma^2 + 1 - 6\gamma/12\gamma - 2\gamma^2 - 2$, $\partial D_{lL}^*/\partial\gamma - \partial D_{eL}^*/\partial\gamma \geq 0$. When $a_l/a_e < \gamma^2 + 1 - 6\gamma/12\gamma - 2\gamma^2 - 2$, $\partial D_{lL}^*/\partial\gamma - \partial D_{eL}^*/\partial\gamma < 0$. And when $1 \geq \gamma \geq 3 - 2\sqrt{2}$, $a_l/a_e \geq 1$, the demand for* *live channels is more affected by γ than the online channel. Otherwise, the opposite is true.*

Proof: to see the appendix.

Proposition 2 shows that when the live broadcast service retention coefficient is large enough, the higher the live broadcast service level is, the greater the demand for live sales channels will be affected by the service retention coefficient, and the market potential of live broadcast sales is also greater than that of online channels. Then the demand for online channels will be less affected. If the initial market potential of the live-streaming retailer is higher than that of the online retailer, then even if the live-streaming sales effect is poor, the online retailer will not be able to obtain market share from the live-streaming retailer. In this case, the live broadcast retailer can overcome the higher live broadcast service overflow, charge higher prices, and generate higher demand. This can be seen in real life. Large-scale live broadcast room sales with a loyal customer base and strong market share are rarely affected by service overflow, even if the live broadcast sales price is higher than other online retail stores. When the live service retention coefficient is less than $3-\sqrt{2}$, the service overflow part will increase; at this time, the market potential of live broadcast sales is smaller than that of online channels. Because online channels have greater market potential than live broadcast sales channels, with greater level of impact on online channels, the final impact level is also related to the retention coefficient of live broadcast services. In real life, small live broadcast rooms will also cause service spillovers, causing consumers to shop at large online retailers. □

3.2. Scenarios OS: Live-Streaming Retailers as Stackelberg Leader. Consider that the online retailer determines the price before the live broadcast retailer, so it is in a leading position in determining the price. Online retailer will preconceive the response of the live broadcast retailer and set their own response. The online retailer is the leader of Stackelberg. For any given wholesale price w and online per retail profit m_e, the live broadcast retailer responds by setting m_l and s. The live broadcast retailer calculates the optimal profit and then sets the price as the sum of the wholesale price and the profit. By maximizing its profit function, the best response of the live broadcast retailer can be obtained. Considering the best response of the live broadcast retailer to its profit function, the online retailer maximizes its profit by setting its profit. Therefore, for a given w, the best responses m_l, m_e, and s are obtained. The following lemma summarizes the best pricing results for live-streaming retailers and online retailer and the best live-streaming service level for live-streaming retailers.

Lemma 2. *Under Scenarios OS, the optimal p_l, p_e, and s can be obtained by the above formula.*

$$\begin{aligned} p_{lE}{}^{*} &= \frac{(3+\gamma)\alpha_l + (2+\gamma)\alpha_e}{4-\gamma^2}, \\ p_{eE}{}^{*} &= \frac{(1+\gamma)\alpha_l + (2+\gamma)\alpha_e}{2}, \\ s_E{}^{*} &= \left(\gamma \frac{(3+\gamma)\alpha_l + (2+\gamma)\alpha_e}{2\left(4-\gamma^2\right)}\right)^2. \end{aligned} \tag{7}$$

Proof: to see the appendix. □

Proposition 3. *The partial derivative of the retailer's price with respect to the service retention coefficient and the price is affected by the service retention coefficient; the higher the service level, the higher the retailer's dual-channel sales price; $\partial p_{lE}{}^{*}/\partial\gamma > 0$ and $\partial p_{eE}{}^{*}/\partial\gamma > 0$. When $a_l/a_e \geq \gamma^4 + 8 - 10\gamma^2 - 8\gamma/12\gamma + 10\gamma^2 - \gamma^4 - 8$, $\partial p_{lL}{}^{*}/\partial\gamma \geq \partial p_{eL}{}^{*}/\partial\gamma$, the impact of live broadcast service overflow on the price of live sales channels is greater than the impact on the prices of online channels; otherwise, the opposite is true.*

Proof: to see the appendix.

Proposition 3 shows that, under the model of online retailers as leaders, retailers will increase the sales prices of the two channels to make profits. When online retailer has greater market potential, they may increase prices on a certain basis after they understand that live broadcast retailer may raise prices. At the same time, the overflow of live broadcast services will have a greater impact on the pricing of live broadcast sales. Furthermore, when the live broadcast sales effect is poor and the service retention coefficient is low, when the online retailer occupies a higher market potential, it will set high prices and occupy a higher market demand share. Under this circumstance, online retailer already has a high market potential, and the overflow of live broadcast services has played a positive role in the sales of online retailer. Therefore, online retailer with higher market potential will benefit more from the overflow of live broadcast services. □

Proposition 4. *With the decision of live sales as the leader, the demand for online channels and live broadcast channels can be derived, and the partial derivation of the demand with respect to the service retention coefficient can be obtained: $\partial D_{lE}{}^{*}/\partial\gamma > 0$, $\partial D_{eE}{}^{*}/\partial\gamma > 0$. It is concluded that, under the pricing decision dominated by online retailers, with the increase in the retention coefficient of live broadcast services, the demand for both channels will increase accordingly; otherwise, the opposite is true.*

Proof: to see the appendix.

Proposition 4 shows that the demand for both channels will increase with the increase of the live broadcast service retention coefficient, and the impact on the live broadcast channel has always been greater than that on the online channel. □

3.3. Nash Equilibrium Analysis. Given the optimal response function of both parties, prove the existence and uniqueness of the Nash equilibrium solution and then further elaborate the decision-making behavior of both parties in the equilibrium state. Given the optimal response function of both parties,

$$m_e = \frac{\alpha_e + m_l + (1-\gamma)\sqrt{s}}{2},$$
$$m_l = \frac{2(\alpha_l + m_e)}{4-\gamma^2}, \tag{8}$$
$$s = \left(\frac{\gamma(\alpha_l + m_e)}{4-\gamma^2}\right)^2.$$

We can solve the optimal prices of the two retailers under Nash game.

Proposition 5. *Under Nash game,* $p_L^* = 2\alpha_l + \alpha_e + (1-\gamma)\sqrt{s}/3 - \gamma^2$, $p_E^* = 4a_l + (4-\gamma^2)\alpha_e + (1-\gamma)(4-\gamma^2)\sqrt{s}/6 - 2\gamma^2$.

Calculating the partial derivatives of s for the prices of two retailers, respectively, we can get $\partial p_e^*/\partial s = (1-\gamma)(4-\gamma^2)/4(3-\gamma^2)\sqrt{s}$, $\partial p_l^*/\partial s = 1 - \gamma/4(3-\gamma^2)\sqrt{s}$, and then $\partial p_{lE}^*/\partial\gamma > 0$, $\partial p_{eE}^*/\partial\gamma > 0$

Taking the retailer's price into the profit function for derivation, we can get $\partial\pi_{lE}^*/\partial\gamma > 0$ and $\partial\pi_{eE}^*/\partial\gamma > 0$. Currently, the game between the two parties constitutes a supermodel game, and the Nash equilibrium solution exists and is unique.

Proposition 5 proves the existence and uniqueness of Nash equilibrium. Meanwhile, from the economic meaning of the supermodel game, we know that the decisions of online retailers are positively correlated with those of live broadcast retailers. Although the live broadcast service efforts of live broadcast retailers will increase the demand of online retailers, at this time online retailers will choose to follow the live broadcast retailers to increase prices and pursue an increase in marginal profits.

4. Comparative Analysis of Different Power Structures

By comparing the profits of retailers in the dual-channel supply chain affected by live broadcast service overflow and market potential, it can be clearly illustrated by drawing a picture.

Figure 1 shows the impact of market potential ratio $\Omega = (a_e/a_l)$ and service retention coefficient on the profits of live broadcast retailer and online retail under the situation of live broadcast retailer as the leader and determines the best areas for the profits of the two retailers. At the top of the curve, the profit of live broadcast retailer is greater than that of online live retailers, and the bottom of the curve is that the profits of online live retailers are greater than the profits of live broadcast retailer. For the part with a low live broadcast service retention coefficient (higher service spillover effect) and the market potential of online retailer being less than that of live broadcast retailer, their profits will be greater than the profits of live broadcast sales. With the increase of the live broadcast service retention coefficient and the decrease of Ω, the profits of live broadcast sales begin to exceed the profits of online retailer.

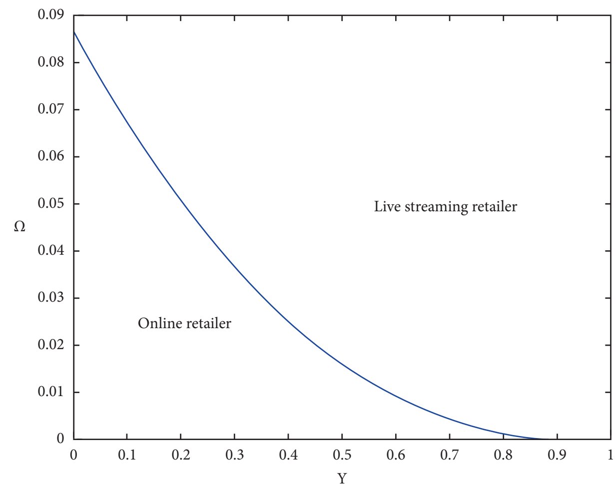


Figure 1: Comparison of dominated area under the leader of live broadcast retailer.

Figure 2 shows that the profits of live broadcast retailer and online retail under the leadership of online retailer are affected by market potential and service retention coefficient. At the top of the curve the profit of online retailer is greater than that of live retailers, and at the bottom of the curve the profit of live retailers is greater than that of online live retailers. It can be found from the figure that even for a low live broadcast service retention coefficient when the market potential of an online retailer is far greater than that of a retailer, its profit will be greater than that of live broadcast sales.

From Figures 1 and 2, we can draw the following conclusions.

Conclusion 1. With a higher relative market potential and a lower level of live broadcast sales service spillover, live broadcast retailer gets higher profits than online retailer. If the market potential of live-streaming retailers is higher than that of online retailer, with a lower level of live-streaming service overflow, live-streaming retailers will get higher profits than online retailers by higher prices and higher profits.

Conclusion 2. With a high relative market potential and a high level of live broadcast sales service overflow, online retailer gets more profits than live broadcast retailer. In the case of a higher level of live broadcast sales service overflow, online retailer will benefit from

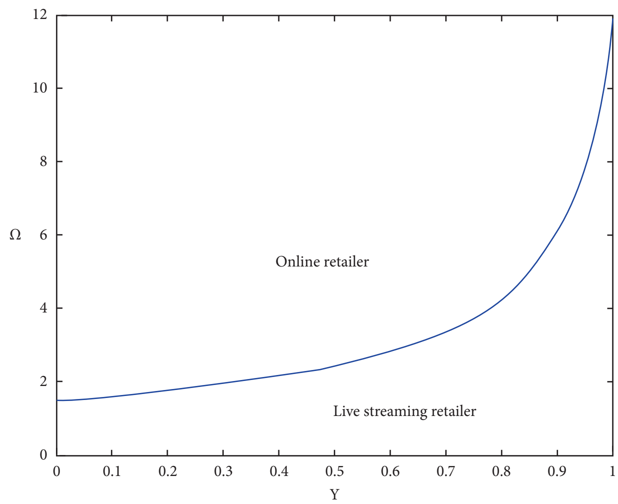


Figure 2: Comparison of dominated area under online retailer.

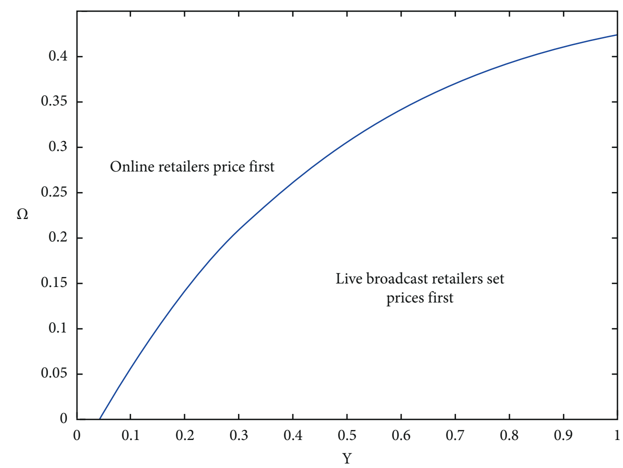


Figure 3: Comparison of dominated area under online retailer as leaders.

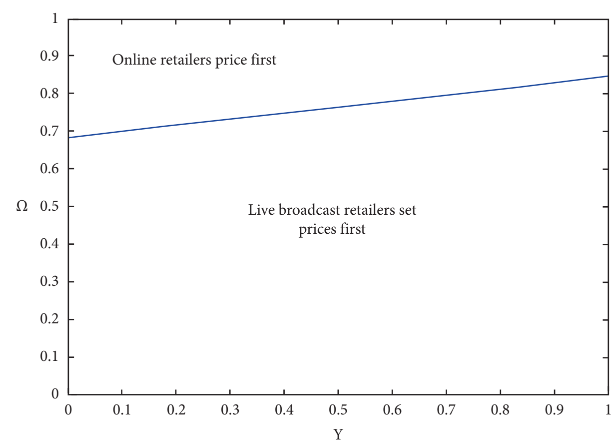


Figure 4: Comparison of online retailer' profit dominated area under different leaders.

the live broadcast services provided by live broadcast sales retailers.

When the market potential of online retailer is low, the advantage of a higher level of the overflow of sales services can be offset by the disadvantage of online retailer' low market potential. When online retailers have higher market potential and a higher level of live broadcast service overflow, they will get higher profits than live broadcast retailer.

Therefore, when the live broadcast retailer has a high degree of its live broadcast service, it will be more beneficial to the live broadcast retailer. When it has higher market potential, it will increase this benefit. On the other hand, when the level of live broadcast sales service overflow is high, online retailer also begins to obtain more revenue, which is supplemented by its higher market potential. Therefore, the interaction between the market potential of live broadcast sellers and online retailer determines which retailer gets higher profits. When live broadcast sales have high market potential, the overflow of live broadcast sales services will have less impact on retailers that conduct live broadcast sales and can give full play to its certain advantages. At this time, the live broadcast retailer can set a higher profit margin, obtain higher market demand, and obtain higher profits.

Figure 3 shows that the profits of live broadcast retailer under different power structures are affected by the market potential and service retention coefficient. At the top of the curve, the profits of online retailer when pricing first are greater than those of live retailers when pricing first, and the bottom of the curve is the opposite. Figure 4 shows the impact of online retailer' profits under different power structures.

From Figures 3 and 4, we can draw the following conclusions.

Conclusion 3. When the relative market potential of live broadcast retailer is high, it is more beneficial for online retailer to price live sales first. At the same time, live broadcast retailer has high relative market potential and can charge higher prices. This also leads online retailer to respond at higher prices and obtain higher profits. However, when the relative market potential of live retailers is low, it will not be able to charge a higher price by setting the price first. At this time, online retailer has obtained higher profits, because online retailer has higher market potential.

Figure 5 shows that the profits of live broadcast retailers and online retailers under the Nash equilibrium are affected by market potential and service retention coefficient. The upper part of the curve shows that the profits of live broadcast retailers are greater than the profits of online live broadcast retailers, and the bottom of the curve shows that the profits of online broadcast retailers are greater than the profits of live broadcast.

5. Extended Models: KOL Introduction

The combination of "Internet celebrity economy" and live broadcast forms a new live broadcast sales model. This kind of live broadcast form adds celebrities or Internet celebrities to sell goods on the basis of traditional live

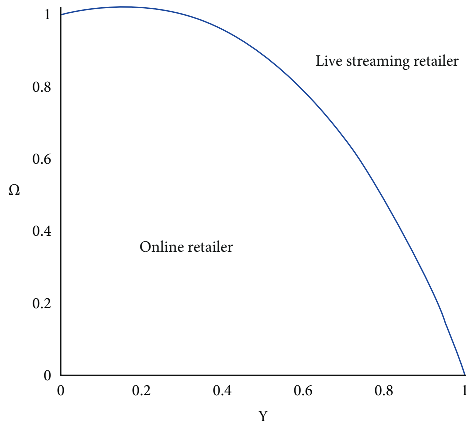


FIGURE 5: Comparison of dominant regions under Nash equilibrium.

broadcast sales, so it often causes consumers to consume impulsively. At the same time, due to the greater influence of Internet celebrities, KOL (Key Opinion Leader) is introduced, and this behavior can be called e-commerce Internet celebrity live broadcast. Therefore, introducing the variable of KOL online celebrity live sales based on live sales may have an impact on the total profit of the supply chain. This article studies the impact of the introduction of Internet celebrity live broadcast by online retailer on their profits.

Assume that online retailer channels introduce KOL live sales and need to hire celebrities or Internet celebrities with a certain fan base for live sales. Assuming that the fixed hire fee of the hired celebrity Internet celebrity is a, the hire fee is a concave function of the number of fans. After the introduction of webcast sales, the new demand will increase by ρ times the original market size, which is a concave function of N. The sales price of the products in the webcast room is p_k, which is given exogenously. At this time, the prices of other channels are p_l, p_e determined in the previous section, which have been given by known parameters and satisfy $p_k < p_l$. Due to the existence of KOL live-streaming offering better prices at this time, some consumers who originally chose the live-streaming sales channel will turn to the KOL live-streaming channel, assuming that the information is asymmetrical, assuming that θ percentage of consumers will actually change the purchase channel. On the basis of the demand function, this article considers that, in the process of cooperating with celebrity Internet celebrity anchors, merchants will pay a commission according to a certain percentage of sales. During the sales process, whenever an Internet celebrity successfully sells a product, the merchant will pay it. The commission rate is r. At this time, the demands of the three channels are

$$\begin{aligned} D_k &= \rho + \theta(p_l - p_k + D_l), \\ D_l'(p_l, s) &= (1-\theta)D_l, \\ D_e'(p_e) &= D_e - \theta(p_l - p_k). \end{aligned} \tag{9}$$

The total profit of online retailer after introducing KOL live sales is

$$\pi_k = (p_e - w)D_e'(p_e) + (p_k - w)D_k - a - cD_k(p_k - w). \tag{10}$$

Lemma 3. *The optimal p_k can be obtained by the above formula.*

$$p_k^* = \frac{\theta m_e + \rho(1-r) + \theta(1-r)(m_l + D_l)}{2\theta(1-r)}. \tag{11}$$

Proposition 6. *Without considering the optimal restriction of θ, the sales price of the KOL live sales channel decreases with the increase of the influence coefficient of the KOL channel.*

Proof: to see the appendix.

Proposition 6 shows that, under the model of joining the KOL live sales channel, the greater the influence of the KOL on the channel is, the lower the price may be. To gain profits, manufacturers can consider asking better KOL to conduct live broadcasts for them. At the same time, they will also reduce the prices of KOL during live broadcasts. In reality, the more famous and the more appealing the KOL live broadcast room is, the lower the price may be. Because of its strong appeal and fan cohesion, KOL has a greater impact on the channel and lower price. The price of the ordinary Internet celebrity live broadcast room is lower due to the lower fan cohesion and appeal, so the influence of KOL on the channel will be smaller, resulting in no price concessions in the KOL live broadcast room. Merchants are also more willing to provide more favorable prices to the more prestigious KOL. □

Proposition 7. *Under the decision of introducing online celebrity live sales, the demand for the online celebrity live sales channel can be obtained. The partial derivation of the demand on the retention coefficient of the online celebrity service can be obtained as $\partial D_k{}^*/\partial\theta = (1-r)(m_l + D_l) - m_e/2(1-r)$, and the size of $\partial D_k{}^*/\partial\theta$ is related to $(1-r)(m_l + D_l) - m_e$. When $(1-r)(m_l + D_l) - m_e > 0$, $\partial D_k{}^*/\partial\theta > 0$, the demand for online celebrity live sales will increase with the influence of the influence of the Internet celebrity channel; otherwise, the opposite is true.*

Proof: to see the appendix. □

Lemma 4. *We can calculate p_k, θ which is the best response to online celebrity live sales:*

$$\begin{aligned} p_k &= \left(\frac{b - \sqrt{b^2 - 4c}}{2}, \frac{b + \sqrt{b^2 - 4c}}{2}\right), \\ \theta^* &= \frac{\rho}{\sqrt{b^2 - 4c}}. \end{aligned} \tag{12}$$

Proposition 8. *When $b^2 - 4c < 0$, the profit of the online celebrity live broadcast room will decrease as θ increases; when $b^2 - 4c > 0$, the positive or negative of the partial derivative of profit to θ is determined by the exogenously given p_k^*; when $p_k^* \in (b - \sqrt{b^2 - 4c}/2, b + \sqrt{b^2 - 4c}/2)$, the profit of the retailer increases with the increase of θ, and vice versa.*

Proof: to see the appendix.

The proposition shows that when $b^2 - 4c > 0$, and only when $p_k^* \in (b - \sqrt{b^2 - 4c}/2, b + \sqrt{b^2 - 4c}/2)$, the retailer's profit will increase with the increase of θ. When the KOL pricing is not within this range, the retailer's profit will decrease with the increase of θ. □

6. Conclusion

With the popularity of online retail and e-commerce platforms, today's consumers can choose between multiple purchase channels. The dual-channel supply chain model that combines online sales channels and traditional retail channels has demonstrated its advantages. However, with the development of technology, the live broadcast sales model began to occupy a large market. Live broadcast sales have gradually become an important means. Consumers can learn about products through the live broadcast room, but they may choose not to buy goods in the live broadcast room. Retailers have created market demand through live broadcast services, but the demand is met through other channels. In the continuously developing live broadcasting market, this paper determines the best pricing decisions of live broadcasting retailers and online retailer and the live broadcasting service level of live broadcast retailer according to the factors such as pricing order, market potential, and live broadcast sales service overflow. Through the analysis and research, three main conclusions are drawn. Firstly, the research shows that live broadcast sales retailers are adversely affected by live broadcast service spillover, but the extent of this impact depends on their market potential. The live broadcast sales retailers with good market potential are relatively less affected by the live broadcast service overflow. Similarly, online retailer with higher market potential will be able to obtain more benefits of live broadcast service overflow than online retailer with lower market potential. Second, contrary to the popular view that live-streaming sales will only affect retailers that conduct live-streaming sales, the research results show that online retailer will be negatively affected by live-streaming sales services overflow. This paper infers that live-streaming sales have an impact on both retailers. The results show that, with the increase of live broadcast sales service spillover, the prices of both retailers will decline. Third, different pricing sequences also have a certain impact on retailers' pricing and profits. When live broadcast retailer has higher market potential, it is more beneficial to set prices first. Different pricing orders can also be used to offset the adverse effects of live broadcast service overflow. From the perspective of consumers, sales services overflow is beneficial because it can reduce overall retail prices. When online retailer introduces KOL live broadcast sales, their profits are affected not only by KOL live broadcasts, but also by the previous pricing. This paper just establishes a general model to analyze multichannel retail under the influence of live broadcast. Customers are nonstrategic, and the model can be extended to places where customers can formulate strategies according to the showroom strength of the price charged by retailers, and there is still more room for expansion.

Appendix

Proof: of Lemma 1

The authors know that the traditional retailer's demand function is $D_l(p_l, s) = a_l - p_l + p_e + \gamma\sqrt{s}$, and the profit function of the live broadcast retailer is

$$\pi_l(p_l, s) == (a_l - p_l + p_e + \gamma\sqrt{s})(p_l - w) - s,$$
$$\pi_l(m_l, s) = a_l m_l - (w + m_l)m_l + s(w + m_e)m_l + s m_l \gamma\sqrt{s} - s. \tag{A.1}$$

Similarly, the demand function of an online retailer is $D_e(p_e) = a_e - p_e + p_l + (1-\gamma)\sqrt{s}$. The profit function of an online retailer is

$$\pi_e(p_e) = (a_e - p_e + p_l + (1-\gamma)\sqrt{s})(p_e - w),$$
$$\pi_e(m_e) = a_e m_e - (w + m_e)m_e + (w + m_l)m_e + m_e(1-\gamma)\sqrt{s}. \tag{A.2}$$

In this setting, the profit function of the online retailer will be solved to find the best response function. Subsequently, the live broadcast retailer found its best response function. The best profit for an online retailer is

$$\mathrm{MAX}\, \pi_e(m_e) = \alpha_e m_e - m_e^2 + m_l m_e + m_e(1-\gamma)\sqrt{s}. \tag{A.3}$$

The first-order condition is $\partial\pi_e/\partial m_e = \alpha_e - 2m_e + m_l + (1-\gamma)\sqrt{s}$, and the second derivative is $\partial^2\pi_e/\partial m_e^2 = -2 < 0$. Therefore, the profit function of an online retailer is a concave function of m_e, so the existence of m_e maximizes the profit. Setting the first-order condition equal to 0, the authors get $m_e = \alpha_e + m_l + (1-\gamma)\sqrt{s}/2$. Based on the above response function, the authors can find the best response of the live sales retailer,

$$\mathrm{Max}\pi_l(m_l, s) = a_l m_l - m_l^2 + m_l\left[\frac{a_e + m_l + (1-\lambda)\sqrt{\theta}}{2}\right] + m_l\gamma\sqrt{s} - s. \tag{A.4}$$

Due to $\partial\pi_l/\partial m_l = 2\alpha_l - 4m_l + a_e + 2m_l + (1+\gamma)\sqrt{s}$, $\partial\pi_l/\partial s = 1/2[(1+\gamma)m_l/2\sqrt{s} - 2]$, the second-order condition is $\partial^2\pi_l/\partial m_l^2 = -2 < 0$, $\partial^2\pi_l/\partial s^2 = -(1+\gamma)m_l/8s^{3/4} < 0$, and $\partial^2\pi_l/\partial m_l\partial s = (1+\gamma)/4\sqrt{s}$. The authors can find that the Hessian of the second-order condition is $H = \begin{bmatrix} \partial^2\pi_l/\partial m_l^2 & \partial^2\pi_l/\partial m_l\partial s \\ \partial^2\pi_l/\partial s\,\partial m_l & \partial^2\pi_l/\partial s^2 \end{bmatrix} = \begin{bmatrix} -2 & (1+\gamma)/4\sqrt{s} \\ (1+\gamma)/4\sqrt{s} & -(1+\gamma)m_l/8s^{3/4} \end{bmatrix} < 0.$

Therefore, the profit function of the live broadcast retailer is the concave function of m_l and s, and there is a unique optimal $m_l{}^*$ and s^* to maximize it. Setting the first-order condition of the retailer's profit function to 0, the authors get two sets of equations: $m_l = 2\alpha_l + \alpha_e +$

$(1+\gamma)\sqrt{s}/2$ and $m_l(1+\gamma) = 4\sqrt{s}$. By solving these two sets of equations and substituting them, the optimal value is obtained.

Proof: of Proposition 1

$\partial p_{lL}{}^*/\partial\gamma = (16\gamma + 16)\alpha_l + (8\gamma + 8)\alpha_e/(7 - 2\gamma - \gamma^2)^2 > 0$, $\partial p_{eL}{}^*/\partial\gamma = (2\gamma^2 - \gamma + 10)\alpha_l + (\gamma^2 - 2\gamma + 5)\alpha_e/(7 - 2\gamma - \gamma^2)^2 > 0$, and $\partial p_{lL}{}^*/\partial\gamma - \partial p_{eL}{}^*/\partial\gamma = (20\gamma + 6 - 2\gamma^2)\alpha_l + (10\gamma + 3 - \gamma^2)\alpha_e/(7 - 2\gamma - \gamma^2)^2$. Therefore, when $a_l/a_e \geq \gamma^2 - 10\gamma - 3/6 - 2\gamma^2 + 20\gamma$, $\partial p_{lL}{}^*/\partial\gamma \geq \partial p_{eL}{}^*/\partial\gamma$; otherwise, it is true.

Proof: of Proposition 2

Due to $D_{lL}{}^* = 4a_l + 2a_e/7 - 2\gamma - \gamma^2$ and $D_{eL}{}^* = (5 - \gamma^2)a_l + (6 - \gamma - \gamma^2)a_e/7 - 2\gamma - \gamma^2$, the authors can get

$\partial D_{lL}{}^*/\partial\gamma = (8\gamma + 8)\alpha_l + (4\gamma + 4)\alpha_e/(7 - 2\gamma - \gamma^2)^2 > 0$, $\partial D_{eL}{}^*/\partial\gamma = (10 - 4\gamma + 2\gamma^2)\alpha_l + (5 - 2\gamma + \gamma^2)\alpha_e/(7 - 2\gamma - \gamma^2)^2 > 0$, and $\partial D_{lL}{}^*/\partial\gamma - \partial D_{eL}{}^*/\partial\gamma = (12\gamma - 2 - 2\gamma^2)\alpha_l + (6\gamma - 1 - \gamma^2)\alpha_e/(7 - 2\gamma - \gamma^2)^2$. Therefore, when $a_l/a_e \geq \gamma^2 + 1 - 6\gamma/ - 2\gamma^2 + 12\gamma - 2$, $\partial D_{lL}{}^*/\partial\gamma \geq \partial D_{eL}{}^*/\partial\gamma$; otherwise, it is true. When $1 \geq \gamma \geq 3 - 2\sqrt{2}$, $a_l/a_e \geq 1$. Otherwise, it is true.

Proof: of Lemma 2

In this setting, the authors solved the profit function of the live broadcast retailer to find the best response function. Subsequently, online retailer found their own response capabilities. The best response from live-streaming retailers is $Max\,\pi_l(m_l, s) = a_l m_l - m_l^2 + m_l m_e + m_l\gamma\sqrt{s} - s$. The authors can get the Hessian (determinant) of the second-order condition as

$$H = \begin{bmatrix} \dfrac{\partial^2\pi_l}{\partial m_l^2} & \dfrac{\partial^2\pi_l}{\partial m_l\partial s} \\ \\ \dfrac{\partial^2\pi_l}{\partial s\,\partial m_l} & \dfrac{\partial^2\pi_l}{\partial s^2} \end{bmatrix} = \begin{bmatrix} -2 & \dfrac{\gamma}{2\sqrt{s}} \\ \\ \dfrac{\gamma}{2\sqrt{s}} & -\dfrac{m_l\gamma}{4s^{3/4}} \end{bmatrix} < 0. \quad (A.5)$$

Therefore, the profit function of the live broadcast retailer is the concave function of m_l and s, and there is a unique optimal $m_l{}^*$ and s^* to maximize it. Setting the first-order condition of the profit function of the live broadcast retailer to 0, the authors get two sets of equations, $2m_l = a_l + m_e + \gamma\sqrt{s}$ and $m_l\gamma = 2\sqrt{s}$. Solving them at the same time, the authors get $m_l = 2(\alpha_l + m_e)/4 - \gamma^2$and $s = (\gamma(\alpha_l + m_e)/4k - \gamma^2)^2$.

Now, the authors find the best response of the online retailer based on the above response function. The first-order condition is $\partial\pi_e/\partial m_e = \alpha_e - 2m_e + (2 + \gamma(1 - \gamma))(\alpha_l + 2m_e)/4 - \gamma^2 = 0$. The authors get the optimal solution.

Proof: of Proposition 3

Due to $\partial p_{lE}{}^*/\partial\gamma = (4 + 6\gamma + \gamma^2)\alpha_l + (4 + 4\gamma + \gamma^2)\alpha_e/(4 - \gamma^2)^2 > 0$ and $\partial p_{eE}{}^*/\partial\gamma = a_l + a_e/2 > 0$, the authors can get

$$\frac{\partial p_{lE}{}^*}{\partial\gamma} - \frac{\partial p_{eE}{}^*}{\partial\gamma} = \frac{\left(12\gamma + 10\gamma^2 - \gamma^4 - 8\right)\alpha_l + \left(8\gamma + 10\gamma^2 - 8 - \gamma^4\right)\alpha_e}{2\left(4 - \gamma^2\right)^2}. \quad (A.6)$$

Therefore, when $a_l/a_e \geq \gamma^4 + 8 - 10\gamma^2 - 8\gamma/12\gamma + 10\gamma^2 - \gamma^4 - 8$, $\partial p_{lL}{}^*/\partial\gamma \geq \partial p_{eL}{}^*/\partial\gamma$; otherwise, it is true.

Proof: of Proposition 4

Due to $D_{lE}{}^* = (3 + \gamma)a_l + (2 + \gamma)a_e/4 - \gamma^2$ and $D_{eE}{}^* = (2 + \gamma - \gamma^2)a_l + (4 - \gamma^2)a_e/2(4 - \gamma^2)$, the authors can get

$\partial D_{lE}{}^*/\partial\gamma = (4 + 6\gamma + \gamma^2)\ \alpha_l + (\gamma^2 + 4\gamma + 4)\alpha_e/(4 - \gamma^2)^2 > 0$, $\partial D_{eE}{}^*/\partial\gamma = (4 - 4\gamma + \gamma^2)\alpha_l/2(4 - \gamma^2)^2 > 0$, and $\partial D_{lE}{}^*/\partial\gamma - \partial D_{eE}{}^*/\partial\gamma = (4 + 16\gamma + \gamma^2)\ \alpha_l + (8 + 8\gamma + 2\gamma^2)\alpha_e/2(4 - \gamma^2)^2$. Therefore, when $0 \leq \gamma \leq 1$, $\partial D_{lE}{}^*/\partial\gamma > \partial D_{eE}{}^*/\partial\gamma$.

Proof: of Proposition 6

Due to $\pi_k = (p_e - w)(D_e - \theta(p_l - p_k)) + (1 - r)(p_k - w)(\rho + \theta(p_l - p_k + D_l)) - a$, the authors can get

$\partial\pi_k/\partial p_k = (p_e - w)\theta \ \ + \rho(1 - r) + \theta(1 - r)(p_l - 2p_k + D_l)$. The authors can get the optimal result by the first-order necessary condition easily.

Proof: of Proposition 7

Due to $D_k = \rho + \theta(p_l - p_k + D_l)$ and $p_k^* = \theta m_e + \rho(1 - r) + \theta(1 - r)(m_l + D_l)/2\theta(1 - r)$, the authors can get $D_k{}^* = \rho/2 - \theta m_e/2(1 - r) + \theta(m_l + D_l)/2$. So, $\partial D_k{}^*/\partial\theta = (1 - r)(m_l + D_l) - m_e/2(1 - r)$.

Proof: of Proposition 8

Due to $\partial\pi_k/\partial\theta = -(p_e - w)(p_l - p_k) + (1 - r)(p_k - w)(p_l - p_k + D_l)$

$$\frac{\partial\pi_k}{\partial\theta} = -m_e(m_l - m_k) + m_k(1 - r)(m_l - m_k + D_l). \quad (A.7)$$

By the first-order necessary condition, the authors can get $m_e + m_l + D_l = b$ and $m_e m_l/(1 - r) = c$, where b and c are given by known parameters.

Data Availability

All data supporting the findings of this study are available within the article.

Conflicts of Interest

All authors declare no possible conflicts of interest.

Acknowledgments

This research was supported by the Ministry of Education of Humanities and Social Science project (18YJA630143).

References

[1] X. Wang, "Understanding user engagement mechanisms on a live streaming platform," in *Proceedings of the International Conference on Human-Computer Interaction*, pp. 266–275, Orlando, FL, USA, July 2019.

[2] Y. Li, X. Li, and J. Cai, "How attachment affects user stickiness on live streaming platforms: a socio-technical approach perspective," *Journal of Retailing and Consumer Services*, vol. 60, Article ID 102478, 2021.

[3] Y. Sun, X. Shao, X. Li, Y. Guo, and K. Nie, "A 2020 perspective on "How live streaming influences purchase intentions in social commerce: an IT affordance perspective," *Electronic Commerce Research and Applications*, vol. 40, Article ID 100958, 2020.

[4] H. J. Park and L. M. Lin, "The effects of match-ups on the consumer attitudes toward internet celebrities and their live streaming contents in the context of product endorsement," *Journal of Retailing and Consumer Services*, vol. 52, Article ID 101934, 2020.

[5] Y. Zhang, T. Shihua, and X. Jing, "Research on consumers' purchase intention on E-commerce live broadcast platform-based on the perspective of social presence," *Contemporary Economic Management*, vol. 43, no. 01, pp. 40–47, 2021.

[6] C. Hong, "Research on marketing strategy of live shopping guide based on customer loyalty," *Business economy*, vol. 11, pp. 90-91, 2018.

[7] D.-Q. Yao and J. J. Liu, "Competitive pricing of mixed retail and e-tail distribution channels," *Omega*, vol. 33, no. 3, pp. 235–247, 2005.

[8] R. Yan and Z. Pei, "Retail services and firm profit in a dual-channel market," *Journal of Retailing and Consumer Services*, vol. 16, no. 4, pp. 306–314, 2009.

[9] Y. Liu, C. Fan, C. Ding, and X. Chen, "Pricing and channel structures selection considering free-riding behavior," in *Proceedings of the 2017 29th Chinese Control and Decision Conference (CCDC)*, May 2017.

[10] K.-Y. Chen, M. Kaya, and Ö. Özer, "Dual sales channel management with service competition," *Manufacturing & Service Operations Management*, vol. 10, no. 4, pp. 654–675, 2008.

[11] E. Brynjolfsson, Y. Hu, and M. S. Rahman, "Battle of the retail channels: how product selection and geography drive cross-channel competition," *Management Science*, vol. 55, no. 11, pp. 1755–1765, 2009.

[12] G. Zhang, G. Dai, H. Sun, and G. Zhang, "Equilibrium in supply chain network with competition and service level between channels considering consumers' channel preferences," *Journal of Retailing and Consumer Services*, vol. 57, Article ID 102199, 2020.

[13] R. Yan, P. Guo, J. Wang, and N. Amrouche, "Product distribution and coordination strategies in a multi-channel context," *Journal of Retailing and Consumer Services*, vol. 18, no. 1, pp. 19–26, 2011.

[14] J. Zhou, P. Shi, and Z. Tang, "Dual-channel pricing strategy based on free rider phenomenon," *Computer Integrated Manufacturing Systems*, vol. 22, no. 4, pp. 1119–1128, 2016.

[15] Y. Liu and Z. Ding, *Revenue Sharing Contract in Dual Channel Supply Chain in Case of Free Riding. Intelligent Decision Technologies*, Springer, Berlin, Germany, 2012.

[16] J. Liu, D. Zhao, and J. Zhao, "Research on channel selection of manufacturers under the influence of free-riding behavior," *Journal of Systems Engineering*, vol. 29, no. 6, pp. 813–823, 2014.

[17] L. Huang, Z. Huang, and B. Liu, "Interacting with strategic waiting for store brand: online selling format selection," *Journal of Retailing and Consumer Services*, vol. 67, Article ID 102987, 2022.

[18] S. Basak, P. Basu, B. Avittathur, S. Sikdar, and S. Sikdar, "A game theoretic analysis of multichannel retail in the context of "showrooming"," *Decision Support Systems*, vol. 103, pp. 34–45, 2017.

[19] B. Dan, G. Xu, and C. Liu, "Pricing policies in a dual-channel supply chain with retail services," *International Journal of Production Economics*, vol. 139, no. 1, pp. 312–320, 2012.

[20] S.-L. Yang and Y.-W. Zhou, "Two-echelon supply chain models: considering duopolistic retailers' different competitive behaviors," *International Journal of Production Economics*, vol. 103, no. 1, pp. 104–116, 2006.