Eng Int Syst (2024) 4: 359–372

Engineering
Intelligent Systems

The Mobile Crowdsourcing-Based Turnover Behavior of Courier Under Community Group-buying Scenario influenced by Interaction and Service Quality

Xiaomeng Ma[1,*], Yi Song[2] and Bin Hu[3]

[1] *College of Economics, Shenzhen University, Shenzhen, 518060, Guangdong, China*
[2] *Shenzhen Natural Resources and Real Estate Appraisal Development Research Center, Guangdong, 518000*
[3] *School of Management, Huazhong University of Science and Technology, Wuhan, 430074, China*

With the widespread usage of mobile devices within growing communities, community group-buying has emerged as a new trend that is gradually changing people's lifestyles. In the traditional Internet environment, the interaction between employees create a type social network. However, as the Internet of Things offers a unique distributed network of location-based interactions between employees and customers, the impact of location-based social networks on the behavior of both parties becomes an interesting issue worth exploring. In this context, we proposed a dual interaction model to discuss the turnover behavior of deliverers in the community group-buying scenario. The results showed that employee-customer interaction led to a two-stage decline in employee turnover, which was different from that in the Internet environment. In order to meet the goal of reducing the rate of employee turnover, it was more appropriate to select the seeding target based on the number of employees' social relationships than to select the seeding target randomly. Results indicated that managers of crowdsourcing logistics enterprises could determine whether employees were worth the corresponding cost and effort by identifying and positioning their degree of social centralization.

Keywords: crowdsourced logistics; employee turnover behavior; opinion dynamics; catastrophe theory

1. INTRODUCTION

In recent years, various natural disasters and public health emergencies have occurred from time to time. During states of emergency, the inter-regional supply chain of products necessary for people to carry on with their usual daily lives and activities can be easily interrupted. The resulting shortage of supplies is likely to cause anxiety and panic among residents, leading to extreme behaviors such as blind buying and hoarding. As natural disasters and other emergencies are on the rise, in a community group buying scenario, products can be purchased and distributed by the community as a unit, which is important for the buying of necessary items during a state of emergency. As a result, community group-buying in China is booming.

Community group-buying involves suppliers deciding the volume of group-buying and commodity prices. The leader of a group-buying community negotiates with suppliers so as to obtain price discounts and valuable services. This form of

*Address for correspondence: Xiaomeng Ma, College of Economics, Shenzhen University, Shenzhen, 518060, Guangdong, China, Email: xiaomengma@szu.edu.cn

group buying is characterized by its regional, localized, and niche focus. During the coronavirus epidemic, community group-buying was a godsend for numerous consumers and to some extent addressed the issue of supply shortages of necessary, everyday products. This confirmed the value of community group-buying.

The supply chain plays a crucial role in community group-buying, and professional delivery services are essential to improving consumers' community group-buying experience. The community group-buying platform offers different modes of distribution, including self-operated distribution, express delivery and third-party distribution. In recent years, advances in Internet technology have led to the rapid development of a sharing economy. In a sharing economy, resources can be used more efficiently more efficient waste of social and inactive resources can be greatly reduced through the integration of platform resources, leading to a new type of logistics known as crowdsourcing logistics [1]. This is seen as a third-party distribution channel in community group-buying, where the existing relatively adequate distribution system is used to distribute the community group-buying products, rather than self-distribution and express delivery, effectively reducing the heavy asset input and logistics cost of the community group-buying platform. In the scenario of community group-buying, the supermarket enterprise or the head of the group-buying community can publish the current logistics needs on the crowdsourcing logistics service platform, so that people who are able and willing to deliver can increase their income, improve the distribution efficiency, and reduce the transportation cost in the last kilometer [2] by competing for orders on the platform. There has been a rapid growth in crowdsourcing logistics platforms, with platforms such as Ele. me "Hummingbird", JD crowdsourcing, Dianwada, Postmates, Uber Rush and other platforms emerging one after another [3].

Crowdsourcing logistics enterprises have a relaxed approach to screening distribution personnel. For instance, people with smart phones and vehicles can begin their distribution job after simple training. However, this high degree of autonomy of distribution personnel poses significant risks for crowdsourcing logistics enterprises. The behavior of employees will directly affect the normal operation of the enterprise and, to some extent, it will also affect the third-party distribution mode in the community group-buying scenario. This may result in the instability of the distribution capacity, negatively affecting the experience of consumers in the community group-buying scheme. One of the primary issues with crowdsourcing logistics is that the delivery is not professional enough and the quality of service is inconsistent, which will lead to the loss of trust of community group-buying platforms and consumers in crowdsourcing logistics enterprises. To address these issues, crowdsourcing logistics enterprises provide users with a system enabling them to evaluate the service provided by each deliverer, so as to obtain comprehensive data on consumers' service experience. Moreover, delivery personnel are held accountable through a rating system, and customers' evaluation of deliverers will in turn affect employees' behaviors.

This work focused on the impact of interaction on employee behavior in crowdsourcing enterprises. It can be seen that, in crowdsourcing logistics, there are two aspects to employees' social relations. On the one hand, in the original Internet environment, the behavioral interaction among employees constitutes a scale-free social network. On the other hand, the embedment of IOT technology enables the interaction between employees and customers to create local, dynamic and location-based social networks. In this work, two interactive process models of crowdsourcing logistics employees are utilized to explore the internal mechanism of employee turnover decision behavior and provide theoretical support for enterprise managers, enabling them to devise and implement effective management control strategies.

To accurately grasp the internal mechanism of employee turnover behavior in crowdsourcing logistics, this work proposes an RA model with embedded catastrophe. Section 2 presents the literature review; in section 3, an analysis is conducted of the online text data of crowdsourcing logistics employees in order to identify the evolution of employees' views based on interactions in an intelligent environment. The construction of the interaction model of customer and employee service evaluation is described in section 4, and includes the embedded mutation RA model used to calculate employee pressure. Finally, we also conducted a series of simulation experiments on the interaction between employers and employees, and between employees and customers in crowdsourcing logistics, so as to analyze the influence of interaction on the evolution of employee turnover decision behavior. Based on the results, several enterprise control strategies are suggested.

Essentially, our study explored the popularization of mobile intelligent devices, and investigated the distribution efficiency and employee turnover behavior mechanism in distributed communities from two perspectives: demand side and supply side. On this basis, we propose a dual interaction model to determine employee turnover behavior in community group-buying scenarios and explore the evolution mechanism of this behavior.

2. RELATED WORKS

2.1 The Distribution Mode in the Community Group-Buying Scenario

The landscape of community group-buying and end-distribution scenarios is continuously evolving, the number of commodity types and consumers is increasing, and consumers' demand for personalized delivery services is growing steadily. To meet consumers' demands for personalized delivery services, community group-buying platforms should build a reasonable distribution system at the end of the supply chain, while crowdsourcing logistics provides a solution to customers' growing demands for quicker delivery time, lower costs, and customization [4]. However, challenges persist in crowdsourcing logistics, including a high concentration of orders and uneven distribution of transportation capacity. Freelance operators are very sensitive to the salaries being offered, so the delivery capacity of crowdsourcing logistics is unstable, which may affect the customer experience of community group-buying [1]. In the e-procurement scenario, Fallah et al. (2023) applied a dynamic genetic algorithm for time optimization, and built a more flexible supply chain system [5]. Pal (2024) studied the supply chain dynamic planning decision problem in multi-cycle mode [6]. Karger et al. (2014) put forward a new algorithm to study the problem of crowdsourcing task allocation in order to minimize the operating cost of logistics system, and obtained the optimal crowdsourcing task allocation scheme [7]. Kung and Zhong (2017) analyzed the profit maximization strategies for bilateral platforms under three different pricing strategies, membership pricing, transaction pricing and cross-subsidy, considering the network externalities [8].

The stability of employee behavior is essential to the third-party distribution mode in community group-buying, which is the issue that is discussed in this work.

2.2 Factors Influencing the Behavior of Deliverers

In this unique distribution logistics mode, the interaction between customers and deliverers is a significant element of the consumption experience. The interaction and turnover behavior of delivery personnel, and quality of communication between employees and customers strongly influences the latter's assessment of the former's services [9,10]. Enterprises whose focus is on customer experience can improve customers' evaluations by strengthening the communication ability and service level of employees. Moreover, customers' praise would in turn sustain the enthusiasm and commitment of service employees [11]. Research has found that employee behavior is not only affected by personal cognition; it is also influenced by social capital [12]. This impact could be facilitated by improving the quality of service, extending working hours or having a positive attitude towards other employees. Social capital, as an opportunity for employees to obtain information from others, could improve cognition as it enables the acquisition of diverse information via social relationships [13]. Therefore, numerous studies have explored the impact of employee interactions on their behavior.

Customer-employee interaction is an important part of services because the generation and purchase of services are non-renewable [14]. These interactions can enhance service experiences and increase customer satisfaction [15]. Yildiz and Savelsbergh (2019) studied the spillover effect of service quality, service scope and delivery capacity of the crowdsourcing food delivery platform [16]. Klumpp (2017) established a crowdsourcing service quality evaluation system that took into account the stability and participation of crowdsourcing logistics service quality, and proposed that the application of crowdsourcing must be flexible, secure and sustainable [17]. However, the service quality that employees offer to customers might constantly be changing, which makes the relationship between customers and employees relatively unstable, and this service quality could change depending on customer evaluations of the service [18].

Therefore, this current study used the customer-employee exchange model to model the intention of employees, and the viewpoint dynamics model to model the social capital of employees. By integrating these two models, we observed the genesis mechanism of employee turnover.

2.3 Catastrophe Theory and Employee Turnover Behavior

Catastrophe theory is a methodology used to study how continuous small changes of independent variables in a system lead to discontinuous sudden changes of dependent variables [19].

Understanding the shifts in employee behavior is integral to comprehending the continuous process of psychological activity, thereby necessitating psychological research into behavior catastrophe and underlying trust. Huang and Feng (2009) used the catastrophe model to investigate the relationship between service quality and conversion cost of choice behavior, and found that service quality and conversion cost are the two main factors affecting choice behavior, and high conversion cost will lead to mutation phenomenon, and it applied the catastrophe model to the field of social psychology to explain social behavior, attitude change and other related change processes [20]. In addition, the random catastrophe theory was applied to quantitatively analyze the catastrophe of individual psychological perception [22]. Huang et al. [23] proposed how to use the folding model and the cusp model to explain the cognitive process. When applying the catastrophe theory to the study of computational organization, Hu and Hu [24] constructed a hybrid cusp catastrophic model of qualitative simulation and quantitative description of employee behavior catastrophe, and found that the combination of the mutation theory and qualitative simulation could effectively reveal the catastrophe mechanism of employee turnover decision behavior. This research methodology was also used to study the reversal of organizational culture [25] and the evolution of organizational psychological contract [26]. or this study, we adopted the cusp catastrophic model to examine the changing characteristics of crowdsourcing logistics employees' viewpoints. We used the cusp catastrophic model to simulate the changes of individual viewpoint uncertainty.

Therefore, on the basis of previous research, we proposed a dual interaction model under the distributed network to discuss the turnover behavior of employees in the community group-buying scenario. Specifically, the distribution platform distributes the orders to the community after preprocessing under the condition of maximizing efficiency and benefits, and the employees of the distribution community efficiently complete the orders under the condition of pursuing returns, as shown in Figure 1.

3. DATA COLLECTION AND PROCESSING

3.1 Data Collection

Baidu Tieba, provided by the Chinese search engine company Baidu, is an online community. Here, bar means someplace

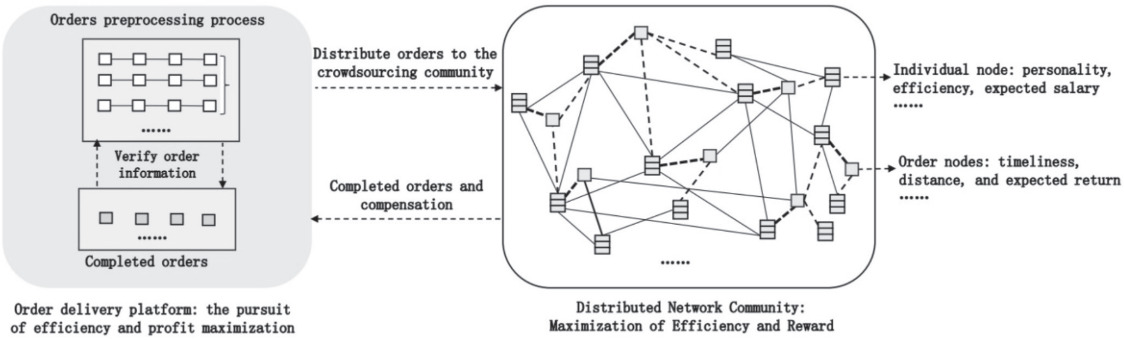

Figure 1 Dual interaction model under distributed network to explore employee turnover behavior.

Figure 2 Word cloud for employees.

on the Internet like a forum providing place for users to do interactive social network site activities. Users are drawn to it as it offers a space to share their views on specific topics. DADA delivery bar was created by its delivery staff. Over 50,000 individuals use this platform and more than 480,000 topics are discussed including working conditions, pay, pressure, problems and so on. Individuals can choose specific topics. Participants can post their opinions and experiences with regard to specific issues that ignite their interest and communicate these to others. We collected individual's' opinions of the DADA crowdsourced logistics company about their work pressures and working conditions from online social media "Baidu Tieba".

3.2 Data Analysis

From the aforementioned platform, we collected more than 30,000 data on topics discussed by and of concern to service providers of crowdsourcing logistics from October 2022 to January 2023, and conducted statistical analysis to create a visualization of topics in the form of a word cloud. As can be seen from Figure 2, the topics that are of most interest to service providers are "remuneration" and "price". These data cover platforms such as Dada, Meituan, Ele. me and Hummingbird. It was not difficult to see that when the compensation offered by the outsourcing logistics platform for their services was lower than their expectations, the service providers would most likely choose other platforms. Service providers also reported high levels of stress in the course of their work, including deception or helplessness when confronted by rude suppliers and customers, which increased their desire to quit.

Initially, we utilized semantic analysis to interpret these opinions, which were indicative of the employees' attitudes towards working at DADA. Drawing upon Timothy and Johns (2019 to 2022) review about job attitudes, the individuals opinions range across five measurements labelled as: "extremely not satisfied", "not satisfied", "somewhat not satisfied", "satisfied", and"very satisfied". If an individual said "I have left the company", this statement indicated"extremely not satisfied". Some said"I will consider quitting my job if the company doesn't improve out working conditions" which indicated "not satisfied". The statement "I can't stand anymore, the location is always wrong" indicated "somewhat not satisfied". The opinion"I think the map is okay"belonged to "satisfied", and the statement "I'm a part-time worker, no matter what the condition is, I will continue working" indicated"very satisfied".

We used BosonNLP to rank these data, two colleagues were asked to check these data; scores ranged from -1 to 1. After their check was completed, we used a consistency test to check their work, determining that the consistency was 90%. In cases where the evaluators' opinions conflicted, we assigned it a value. Through this method, we determined the numerical interval of these five classifications as shown in Table 1.

The collected data are shown in Figures 3 and 4.

Figures 3 and 4 indicate that following an initiation of a topic about work pressure and conditions, the individuals' discussions continued for an average of twelve days before their opinions started to stabilize. Figure 2 shows that the evolution of group opinion is stable in two subgroups.

Table 1 The divided interval of opinion.

The interval of opinion	Key words	Description
$(-1, -0.7)$	Extremely unsatisfied	the individual will quit his job immediately
$(-0.7, -0.4)$	Not satisfied	the individual will quit his job if the working conditions worsen or the work pressure becomes higher
$(-0.4, 0)$	Somewhat unsatisfied	the individual is dissatisfied with the company but will not quit his job
$(0, 0.5)$	Satisfied	the individual understands the difficulty of the company and will not reduce his enthusiasm for the job
$(0.5, 1)$	Very satisfied	the individual will work harder

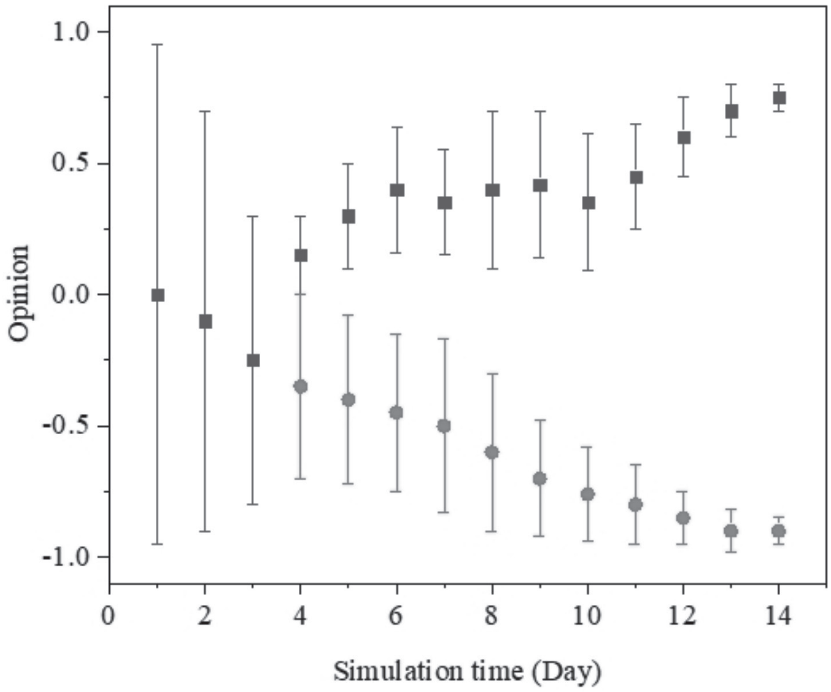

Figure 3 The evolution of global opinion.

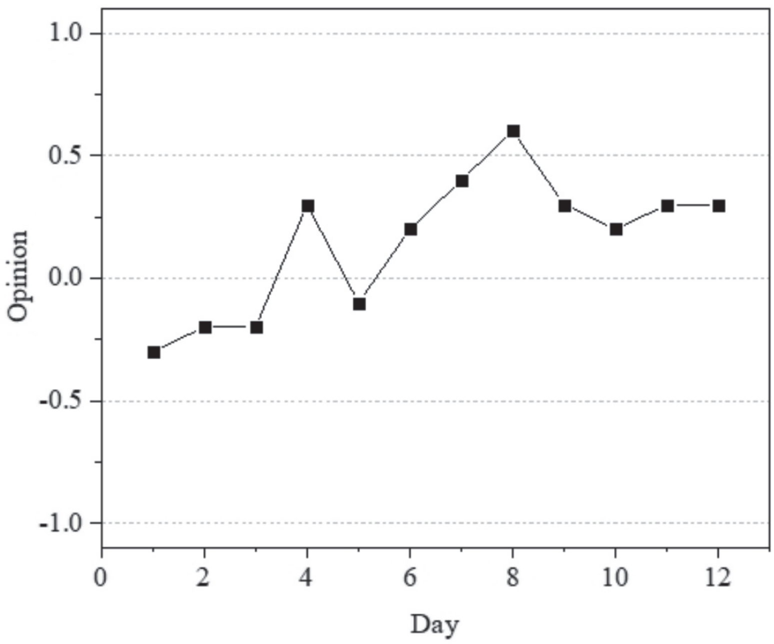

Figure 4 The evolution of an individual's opinion.

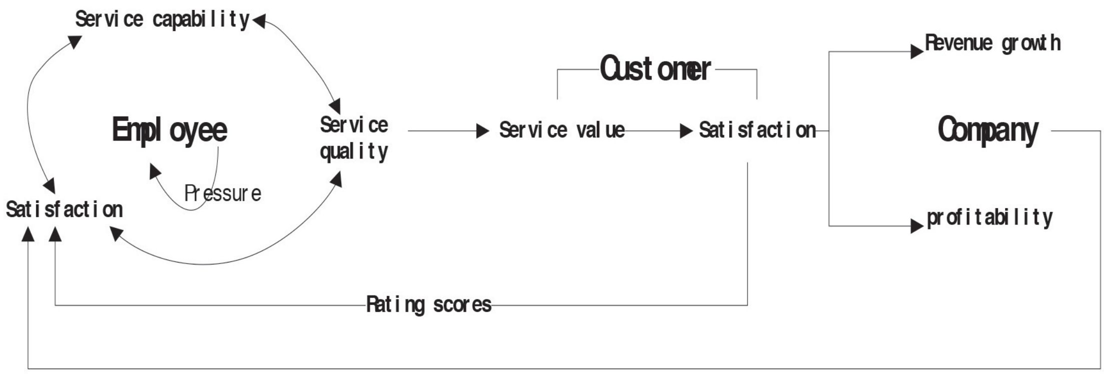

Figure 5 Service profit chain of employee-customer linkage.

We observed that some individuals' opinions and statements suddenly change from positive to negative, other individuals' opinions are barely influenced, and yet others' statements and opinions are influenced only by certain specific opinions.

4. CUSTOMER-EMPLOYEE INTERACTION MODEL

A critical aspect of the interactive relationship in crowdsourcing logistics enterprises is a service profit chain based on employee satisfaction, customer satisfaction and enterprise profitability. We focused on employee satisfaction and customer satisfaction, and established a conceptual model according to a "service profit chain" [27] as shown in Figure 5.

According to the service profit chain, the company's business strategy and service delivery system determined the service ability of the company's employees, that is, their ability to meet the needs of customers. High-quality service from employees enhances customer satisfaction with the service value, creating a positive correlation between service value and customer satisfaction. The customer rates the employee based on his level of satisfaction with the service, and the rating subsequently affects the employee's satisfaction. Moreover, in the community group-buying scenario of crowdsourcing logistics distribution mode, after the transaction is completed, customers rate employees, which can directly determine the maximum number of orders that employees receive every day; hence, the rating will affect the income of both employees and enterprises. In the real world, via the Internet, employees communicate with other employees about how stressed they are at work, and these interactions also affect employee satisfaction. In this study, we focused primarily on the impacts of these interactions between employees and other employees or customers.

4.1 Employee-Customer Exchange Model

In regard to practical decision-making, a crowdsourcing logistics employee exhibits bounded rationality, implying that they cannot always make optimal decisions. For instance, they may feel satisfied if their income surpasses their expectations. To determine the optimal strategy, the employee must have a comprehensive knowledge of the way the system operates, as well as the strategies used by other employees, which is very difficult. Even if the employee has access to all the information, it may still be challenging for them to arrive at an optimal strategy. In an intelligent environment, tasks are published in real time, and the deliverer has limited time to respond, lacking both the time and computing power to make the optimal decision. Considering the bounded rationality of employees, we opted to use the RA model to simulate the interaction between employers and employees.

The Rational Actor (RA) model yields three possible evolutionary outcomes: convergence towards the center, convergence towards two poles, or single extreme convergence. In this current study, our investigation was strongly focused on the relationship between employee job satisfaction and customer satisfaction, using data linking employee responses with customer responses. The accumulated research includes findings of a positive [28, 29], negative [30], and non-significant relationship. Hence, we divided employees into three types. We conducted time tracking and dynamic analysis of the employee data collected in the early stage. Using this process, we identified three types of employees. This process helped us to identify three distinct types of employees. The first type used the evaluation of the organization as a means of increasing their motivation, That is, if the rating was lower than the service quality required, they would strive to improve their service quality so as to achieve higher evaluations. We call these individuals 'positive employees'. The second type of employee thought that the evaluation of the organization was a punishment; that is, if the rating was lower than the service quality, they feel angry and reduce the service quality; these individuals are 'negative employees'. The last group of employees falls somewhere in between. These are called 'non-significant employees' as the ratings they received did not change the quality of service they provided. According to the theory of bounded rationality, individuals are inclined to believe that their benefits are outweighed by their costs. Therefore, the situation where the rating is higher than service quality falls outside the scope of this work. The process is shown in formula (1).

If $\frac{rating\_score}{service_quality} < 1$, in the next time, the employee's service quality is:

$$\begin{cases} service\_quality_t = service\_quality_{t-1} & \text{Non-significant employee} \\ service\_quality_t = service\_quality_{t-1} \\ \quad * \left(1 + \left(1 - \frac{rating\_score_{t-1}}{service\_quality_{t-1}}\right)\right) & \text{Positive employee} \\ service\_quality_t = service\_quality_{t-1} \\ \quad * \left(1 - \left(1 - \frac{rating\_score_{t-1}}{service\_quality_{t-1}}\right)\right) & \text{Negative employee} \end{cases} \tag{1}$$

where *service_quality* and *rating_score* is from 0 to 10.

Employee service quality influenced customer perceptions of service value, an service value had a positive association with customer satisfaction. We observed that in terms of customer rating, the customer compares the last two experiences, and then gives a rating, seen in formula (2).

$$\begin{cases} rating\_score_t = Uniform(0, service\_quality_t \\ +(service\_quality_t - service\_quality_{t-1})) \\ \quad service\_quality_t > service\_quality_{t-1} \\ rating\_score_t = Uniform(0, service\_quality_t \\ -(service\_quality_t - service\_quality_{t-1})) \\ \quad service\_quality_t < service\_quality_{t-1} \end{cases} \tag{2}$$

The rating determines the number of orders that an employee will receive, while the pressure determines the number of orders that an employee wants to deliver. Then we used the catastrophe-embedded RA model to calculate employees' pressure.

4.2 Catastrophe-Embedded RA Model

During interactions, individuals exchanged opinions containing state variable values. The opinions and their associated uncertainties were modified during interactions according to the relative agreement model (RA model). In the RA model, randomly-selected pairs of agents interacted, expressing their opinions and their confidence in those opinions, and each agent then updated their own opinion on the basis of the new information. The uncertainty represented the individual's confidence in their opinions. The viewpoints of the original RA model evolved continuously, while the viewpoint of the DADA employees we collected had intermittent changes, with some abrupt changes. We believed that this discontinuity may be caused by the degree of individual uncertainty. The sudden changes in opinion can be explained using catastrophe theory.

In the RA model, the initial value of uncertainty obeyed uniform distribution under (0, 0.5). However, in reality, the confidence was influenced by individual heterogeneity and the external environment. We found that some individuals' opinions may suddenly change from a positive state to a negative state, while the opinions of other individuals were barely influenced, and yet others were influenced only after reading someone's statement about a specific issue. Many applications to problems of social science have since appeared, such as discontinuities in psychology, in organizations and in the economy in terms of catastrophe theory. Flay's analysis demonstrated that the cusp catastrophe model was done a better job of describing a change in human behavior [21]. Certain studies on job satisfaction have suggested that it can be modeled using cusp catastrophe theory. The behavior surface was employee's satisfaction state, the normal factor u was the competence or skill of the supervisor or management, and the splitting factor v was the employee's involvement in their jobs. In keeping with this research, we have defined the normal factor u as the sensitivity of perceiving pressure, and the splitting factor v as the working conditions.

We set u, v obeyed uniform distribution under $(-1, 1)$, $\alpha = 1.4137$, $\beta = 1.2130$ (the calculating algorithm was based on Hu and Xia [24], through the formula (3) got f.

$$f^3 + \alpha \cdot u \cdot f + \beta \cdot v = 0 \tag{3}$$

The result showed that the value of f was between $(-3.1, 0)$, in order to conform to the original RA model, we standardized f to $(0, 0.5)$

$$u_i = 0.5 \cdot \cos\left(f + \frac{\pi}{2}\right) \tag{4}$$

We considered a population of N Agent, each agent i is characterized by two variables, its opinion x_i and its uncertainty u_i, and the opinion segments are $[x_i - u_i, x_i + u_i]$, h_{ij} is defined as the opinion overlap of agent i and agent i.

$$h_{ij} = \min(x_i + u_i, x_j + u_j) - \max(x_i - u_i, x_j - u_j) \tag{5}$$

If $h_{ij} > u_i$, then the modification of x_j and u_j by the interaction with i is:

$$x_j = x_j + \mu \cdot \frac{d_i}{d_j} \cdot \left(\frac{h_{ij}}{u_i} - 1\right) \cdot \left(x_i - x_j\right) \tag{6}$$

$$u_j = 0.5 \cdot \cos\left(f_j + \frac{\pi}{2}\right) \tag{7}$$

where μ is a constant parameter which amplitude controls the speed of the dynamics. If $h_{ij} < u_i$, there is no influence of agent i and agent j. We add d_i/d_j in the RA model to simulate the influence of the node. In reality, we tend to focus on and trust on the individual who has lots of neighbors on the Internet. The greater of d_i/d_j means the agent i have more influence on agent j. Through the RA-catastrophe model, we can calculate individuals' opinion after one step communication and then we will test and verify the model.

4.3 Agent-Based Model

We established a virtual context consisting of a social network of employees and customers as agents. The agents are autonomous, interactive, and have bounded rationality.

Using this model, we calculated each employee's pressure level. As previously discussed, the rating score determines the number of orders that an employee will receive, while the pressure determines the number of orders that an employee wants to deliver. We normalized the rating score and employees' pressure to the same range for comparison. If rating score was less than the employee's pressure, meaning that the employee could receive as many orders as he wanted, he might not receive adequate wages and therefore might

Table 2 Initial values of experiment parameters.

Parameters	Initial values
Number of employees, N	2000
Number of customers, M	3000
Network structure of employees	Scale free network
Network structure of customers	Location based network
Simulation time	100
Simulation times	30

consider leaving the company. The probability of an employee leaving is calculated with $\frac{opinion-rating\_score}{rating\_score}$. The opinion represents employee's pressure, and the employee's pressure is inversely proportional to the employee's opinion. The rating score represents the upper number of orders that the employee can get for a day.

The interactions among employees occur online, research indicates that the structure of the web and social media is a scale-free network. Characterized by a short average path length and a high network clustering coefficient, the degree distribution of this network structure also adheres to the power law. [31]. We considered the network structure as a scale-free network and set the minimal number of neighbors to 4 when using preferential topology set according to the empirical data.

The interaction between employees and customers is fundamentally different from the interaction between employees. Crowdsourcing logistics makes use of intelligent terminal software based on geographical location and a location-positioning service, providing a foundational framework for assigning distribution tasks. Shipping orders are preferentially matched according to the geographic location of employees and customers [32]. Consequently, we devised a location-based network structure comprising employees and customers so that they will connect only when they are in close proximity.

5. RESULTS

In this section, we present a series of experiments simulating the interaction between employee and employee, and employee and customer. The results provide powerful support for the theoretical analysis. The simulation tool was Anylogic 6.4.1. Table 2 shows the initial values of the experiment parameters.

5.1 Validation of the Agent-Based Model

Empirical studies traditionally derived results through questionnaires, designed experiments or observational data. On the other hand, modeling and simulation (ABMS) approaches use computer simulation to study the macro evolutionary dynamic characteristics of the whole system by simulating the interaction between individuals [33–35]. The researchers have recently developed a systematic framework procedure for testing the ABMS model, which will be used in this paper to verify our model simulation results.

5.2 Face Validation

Face validation refers to subjective evaluation whereby the model subjectively covers the variables to be measured. That is, if a model contains the variables to be studied, then it has surface validity. When conducting simulation, the primary goal is to build a system that can support experiments and record the changes of each variable to be measured during simulation. We constructed the framework, parameters and decision-making process of the model based on relevant research literature, and met the requirements of surface validity.

5.3 Empirical Input Validation

This step ensures that the data entered into the simulation model is realistic and valid. Through empirical research and support provided by actual data support, we achieved the validity of input data.

5.4 Empirical Output Validation

The output validity refers to the verification of the output results of the simulation model and the findings in the real world. Figures 6, 7 and 8 show the simulation results of RA model with embedded catastrophe.

Figure 6 illustrates the evolution of each individual's opinions under the catastrophe-embedded RA model. The evolution of employee opinion can be divided into three types. Type B represents a situation where an individual's uncertainty varies, changing according to the internal and external factors (cusp catastrophe model); therefore, the individuals' opinions appear to oscillate. Type A and type C individuals are those whose psychological states were in either a normal state or an abnormal state; that is, when the individual's psychological state was more stable, their opinions were affected more strongly by other individuals, as shown in Figure 7.

Compared with Figure 8, we found that the simulation results of the catastrophe embedded RA model were very close to the empirical data. As shown in Table 3, the correlation between the results of RA-catastrophe and empirical data is 0.973. This value exceeds 0.95, demonstrating a strong similarity between these two data sets.

The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used when comparing two related/matched samples. It is an alternative to the paired Student's t-test, t-test for matched pairs, or the t-test for dependent samples when the population cannot be assumed to be normally distributed. Table 4 shows the results of the Wilcoxon signed-rank test.

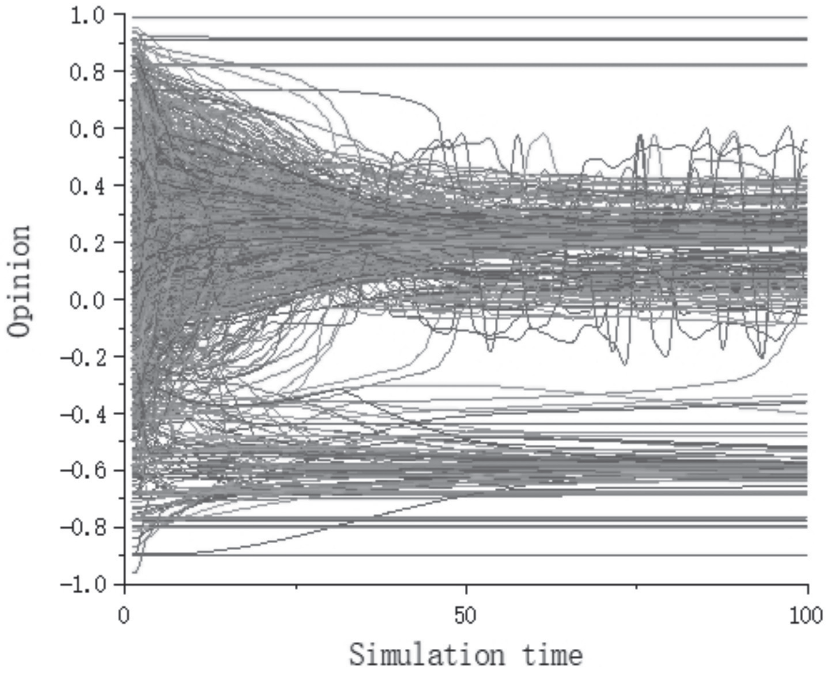

Figure 6 Behavior evolution of various types of employees.

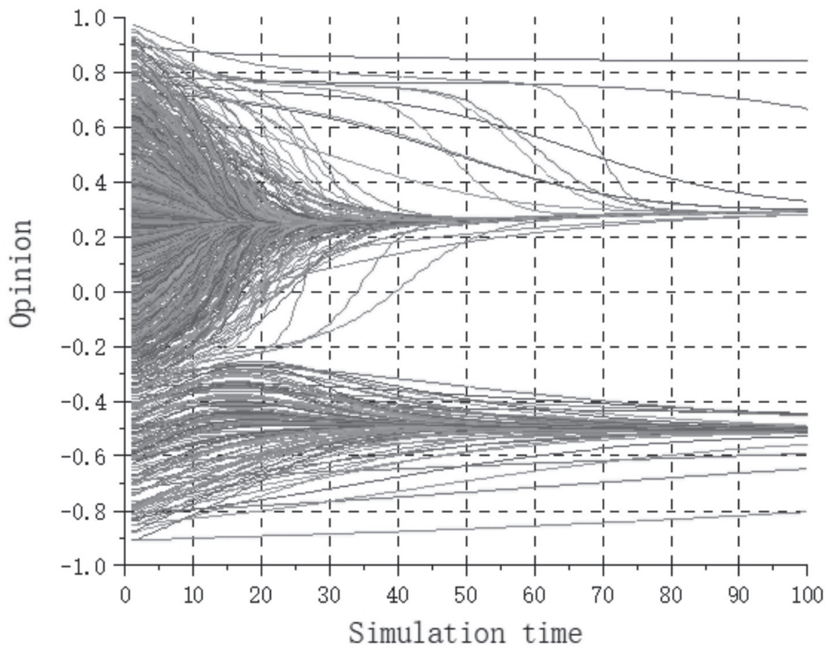

Figure 7 Behavior evolution of Type A and Type C employees.

As shown in Table 4, the P value is 0.430, which is considerably greater than 0.05, indicating that the simulation data was not significantly different from the real data. Hence, the proposed catastrophe-embedded RA model is reliable and effective.

5.5 Simulation Experiment Results

As previously stated, the employees' decision to leave the company was based on their pressure rating and the customers' rating score. Hence, we determined how these two factors impact employees' turnover rate. Table 5 shows the correlation between these two factors and employees' turnover rate.

Table 5 shows that customers' rating scores are inversely proportional to employees' pressure and turnover rate, while employees' pressure is directly proportional to turnover rate. Employees' pressure has greater impact on employees' turnover rate than do customers' rating scores. Consequently, our focus shifts to addressing these two influential factors separately and determining strategies to reduce the employee turnover rate.

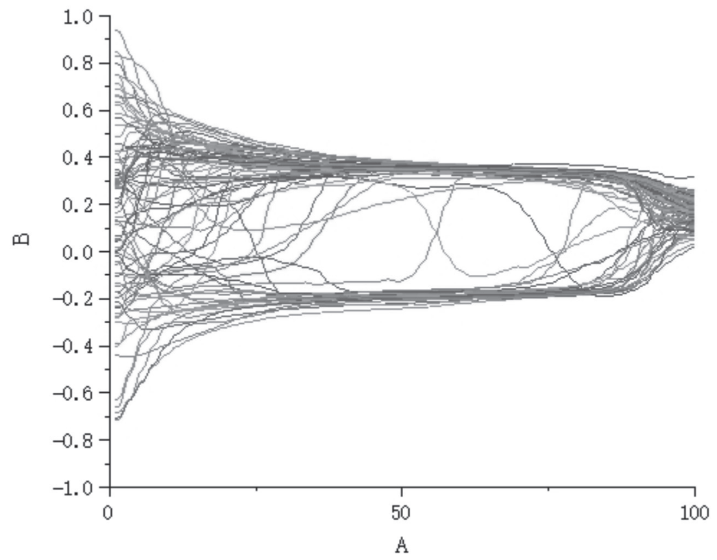

Figure 8 Behavior evolution of Type A and Type C employees.

Table 3 Paired samples correlations.

	Correlation	Sig.
Model & reality	**.978**	.000

Table 4 Wilcoxon signed-rank test.

	Model – Reality
Z	−.824
Asymp. Sig. (2-tailed)	.430

Table 5 Correlation analysis of employees' turnover rate.

	Customer's rating score	Employee's pressure	Employees' turnover rate
Customer's rating score	1		
Employee's pressure	−0.356	1	
Employees' turnover rate	−0.413	0.805	1

5.6 Control Strategy Between Employee and Employee Interaction

Network intervention involves leveraging data from social networks to accelerate the process of changing or improving organizational performance. Many network intervention strategies have been proposed, including various mathematical algorithms. So, there are numerous options for intervention available according to the characteristics of network data, perceived behavior, and social background. The most commonly-used network intervention strategy is to examine network data in order to identify the opinion leaders in the network, and influence other individuals in the network by changing the opinions of these leaders [36,37]. Multiple studies have suggested that the top 10% to 15% of individuals in the number of neighbor nodes in a social network could be regarded as opinion leaders. Another intervention strategy is random intervention, which does not consider the attributes of the individuals involved in the intervention, but selects them randomly. This strategy represents the influence of general individuals in the network on the network [38]. The experiment design is presented in Table 6.

The results are shown in Figure 9.

Figure 9 illustrates the effectiveness of the intervention strategies on employee turnover rates in the network. The intervention results show that the employee turnover rate is lower after intervention, which is consistent with the findings of previous studies [39, 40]. Furthermore, our analysis found that for both intervention strategies, when controlling the top 10% of individuals in the network, the turnover rate of employees is lower than that of the top 5%. However, when the number of individuals in the control network reaches 15%, the differences between the two strategies begin to emerge. For random intervention, the turnover rate of employees still declines, while for opinion leader intervention, the turnover rate of employees begins to rise. Therefore, we predict that the two intervention strategies applied to the employee turnover rate would be represented by a U-shaped structure.

In order to find the "optimal" intervention size, we studied the effect of intervention size on turnover rate.

Table 6 Control strategy for employee and employee interaction.

Control strategy	Parameter value
Social hubs	5%, 10%, 15%
Randomly chosen	5%, 10%, 15%

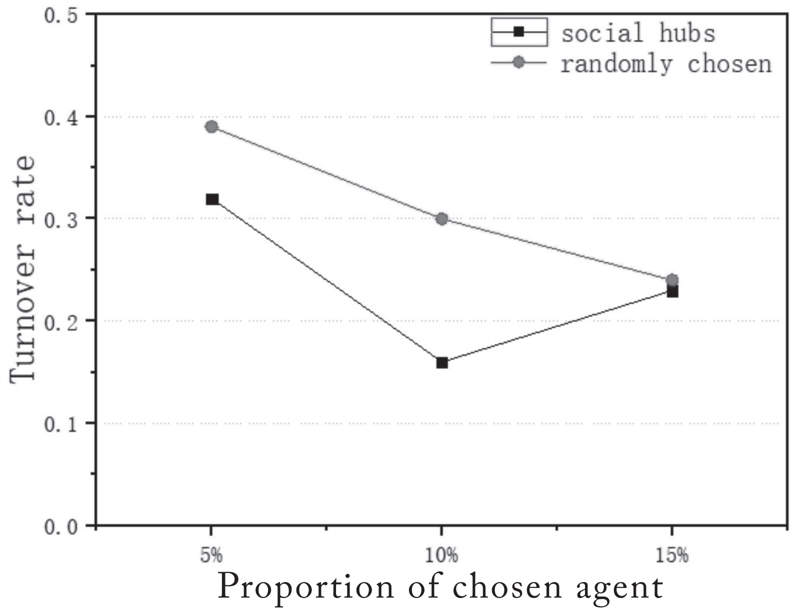

Figure 9 Employees' turnover rate under different control strategy of employee and employee interaction.

Table 7 The optimal choosing size for alternative seeding targets.

Control strategy	Optimal choosing size
Random	9%–20% (16%, 0.207)
Social hubs	6%–14% (11%, 0.139)

We determined the optimal intervention size for the two intervention strategies, as shown in Table 7.

Our analysis found that the effectiveness of the intervention strategy on employee turnover rate was significant when the intervention scale of random intervention is between 9% and 20%, the intervention strategy had a significant impact on the employee turnover rate. When the intervention scale is 16%, the employee turnover rate is the lowest, which is 20.7%. Additionally, when the intervention strategy is adopted for opinion leaders, when the intervention scale is 11%, the turnover rate was the lowest, which is 13.9%. The findings presented in Table 7 also confirmed the U-shaped relationship between employee turnover rate and intervention scale.

Observation 1: *Nodes with more social relations should be chosen purposefully rather than randomly for control. Managers of crowdsourcing logistics enterprises can choose the optimal intervention scale for opinion leaders to develop corresponding management control strategies.*

5.7 Sensitivity Analysis Between Employee and Customer Interaction

Crowdsourced logistics is also known as 'location-based crowdsourcing' (LBCS). Individuals who are located close to a specific area are assigned tasks that are related to that location. [41]. The interaction between employee and customer takes place within a distance-based network. In this part, we explored how employees' range of movement (work territory) influences the rate of employee turnover.

In an IoT environment, the interaction between employee and customer is partial, dynamic, and based on their location. While under the Internet environment, a person's neighbors will not change with the location.

We set the moving range from 1 to 10; results are shown in Figure 10.

Figure 10 shows that the turnover rate decreases as the rating score increases, which confirms the correlation analysis of employee turnover rate. From a marketing perspective, it is crucial to acknowledge that customers are not always right – in fact, they are often wrong – and when they are, their unfair ratings could be demoralizing to front-line service providers. For front-line work, managers of crowdsourcing logistics companies should be aware that motivated and passionate front-line employees can expand and retain a loyal customer base for the company. In this study, we found that the customers' rating scores were inversely proportional to employees' pressure and turnover rate, but some customers consistently give lower ratings, so the company cannot rely solely on the customers' feedback to evaluate their employees.

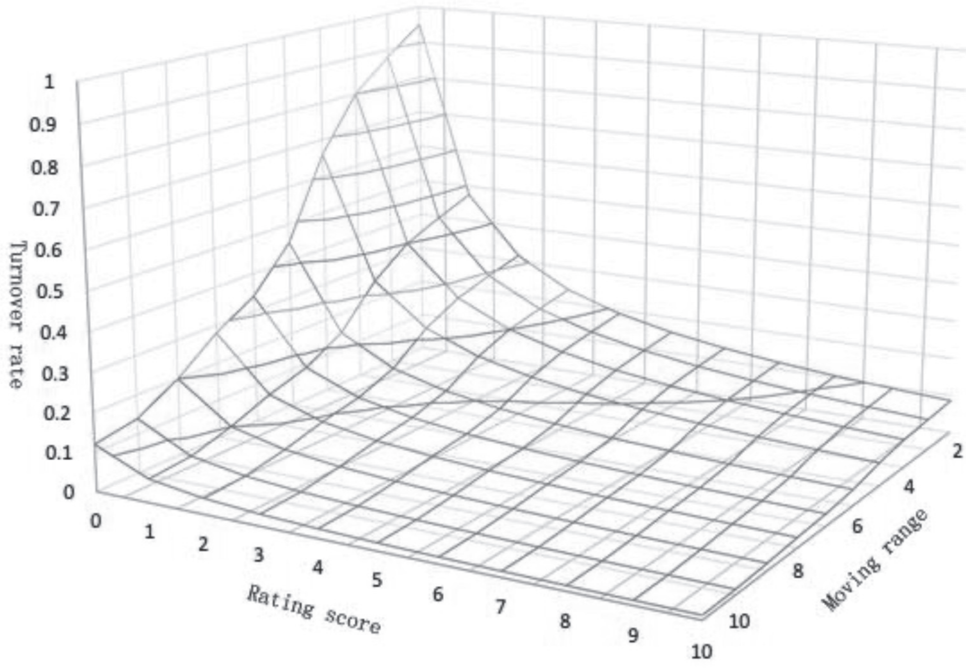

Figure 10 Turnover rate under different moving range and rating score.

With the moving range increases, the turnover rate fell quickly during the first period and then fell slowly during the next period. Hence, when the movement range of an employee increased from 1 to 5, the number of customers contacted by the employee increased substantially, and this increase led to an increase in the difference of customer ratings. However, it was also found that there was less likelihood of high turnover rates among employees with a fair service rating if they had a larger customer base. But when employee's moving range (territory) increased per unit from 5 to 10, the growth rate in the number of customers was not as substantial, leading to a slower reduction in the turnover rate.

In conclusion, our research results show that the company should encourage employees to expand the delivery radius to reduce the turnover rate, but sometimes, the turnover rate is not the lower the better, so the company needs to seek the optimal scheme in the turnover rate and delivery area under the corresponding incentive measures.

Observation 2*: In the smart environment, the interaction between employee and customer is partial, dynamic, and based on their location, demonstrating a two-stage downward trend in the rate of employee turnover.*

6. CONCLUSION

We used a computational approach to capture and trace the changes in employees' turnover behavior in a crowdsourced logistics company. In this work, we explored the impact of two types of interactions: employee and employee interaction which was under Internet environment, and employee and customer interaction which was under intelligent environment on the employee's turnover behavior.

(1) In order to decrease the employee turnover rate, we found that it was better to deliberately choose nodes with more social relations than to randomly select nodes for control in the employee and employee interaction in the Internet environment. Managers of crowdsourcing logistics enterprises can choose the optimal intervention scale of opinion leaders to develop corresponding management control strategies.

(2) It was observed that the employee and customer interaction in an intelligent environment, is partial, dynamic, and based on their location, and leaded the employee's turnover rate exhibits two-stage down trend.

According to the aforementioned service profit chain, we considered only the relationship between employee and employee, employee and customer. In the future, we will explore the interaction and impact between employee, customer and company.

ACKNOWLEDGEMENTS

This work was supported by a Discipline Co-construction Project grant from Guangdong Planning Office of Philosophy and Social Science (No. GD22XYJ10), a Youth Science Foundation Project and a General Program grant from the National Natural Science Foundation of China. (No. 72101158, 71971093), and a General Project grant from the Shenzhen Science and Technology Innovation Commission Stability Support Program (No. 20220811153252002), and the Open Fund of Key Laboratory of Urban Land Resources Monitoring and Simulation, Ministry of Natural Resources, Research on industrial evolution analysis and spatial optimization strategy based on urban residents' behavioral decision, KF-2021-06-093.

REFERENCES

1. Meng Xiuli, Liu Bo, An Kun. Selection of crowdsourcing logistics operation mode considering deliverer interaction and service quality [J/OL]. Chinese Journal of Management Science: 1–15[2023-04-30]. DOI:10.16381/j.cnki.issn1003-207x.2021.2508.
2. Bai J, So K C, Tang C S, et al. Coordinating supply and demand on an on-demand service platform with impatient customers[J]. Manufacturing & Service Operations Management, 2019, 21(3): 556–570.
3. Qi W, Li L, Liu S, et al. Shared mobility for last-mile delivery: Design, operational prescriptions, and environmental impact[J]. Manufacturing & Service Operations Management, 2018, 20(4): 737–751.
4. Alnoor A, Tiberius V, Atiyah A G, et al. How positive and negative electronic word of mouth (eWOM) affects customers' intention to use social commerce? A dual-stage multi group-SEM and ANN analysis[J]. International Journal of Human–Computer Interaction, 2024, 40(3): 808–837.
5. Fallah P, Rabiee M, Yousefi-Babadi A, et al. Designing an Agile, flexible and resilient disaster supply chain network using a hybrid group decision-making robust optimization framework[J]. Computers & Industrial Engineering, 2023, 184: 109591.
6. Pal B. Impact of prices and collection rivalry in a sustainable closed-loop dual-channel supply chain under different power configurations[J]. International Journal of Systems Science: Operations & Logistics, 2024, 11(1): 2297222.
7. Karger D R, Oh S, Shah D. Budget-optimal task allocation for reliable crowdsourcing systems[J]. Operations Research, 2014, 62(1): 1–24.
8. Kung L C, Zhong G Y. The optimal pricing strategy for two-sided platform delivery in the sharing economy[J]. Transportation Research Part E: Logistics and Transportation Review, 2017, 101: 1–12.
9. Mägi A W. Share of wallet in retailing: the effects of customer satisfaction, loyalty cards and shopper characteristics[J]. Journal of retailing, 2003, 79(2): 97–106.
10. Bowen D E, Lawler III E E. Empowering service employees[J]. MIT Sloan Management Review, 1995, 36(4): 73.
11. Pugh S D, Dietz J, Wiley J W, et al. Driving service effectiveness through employee-customer linkages[J]. Academy of Management Perspectives, 2002, 16(4): 73–84.
12. Shalley C E, Gilson L L. What leaders need to know: A review of social and contextual factors that can foster or hinder creativity[J]. The leadership quarterly, 2004, 15(1): 33–53.
13. Zhou J, Shin S J, Brass D J, et al. Social networks, personal values, and creativity: evidence for curvilinear and interaction effects[J]. Journal of applied psychology, 2009, 94(6): 1544.
14. Ma E, Qu H. Social exchanges as motivators of hotel employees' organizational citizenship behavior: The proposition and application of a new three-dimensional framework[J]. International journal of hospitality management, 2011, 30(3): 680–688.
15. Namasivayam K, Mattila A S. Accounting for the joint effects of the servicescape and service exchange on consumers' satisfaction evaluations[J]. Journal of Hospitality & Tourism Research, 2007, 31(1): 3–18.
16. Yildiz B, Savelsbergh M. Service and capacity planning in crowd-sourced delivery[J]. Transportation Research Part C: Emerging Technologies, 2019, 100: 177–199.
17. Klumpp M. Crowdsourcing in logistics: An evaluation scheme[C]//Dynamics in Logistics: Proceedings of the 5th International Conference LDIC, 2016 Bremen, Germany. Springer International Publishing, 2017: 401–411.
18. Sierra J J, McQuitty S. Service providers and customers: social exchange theory and service loyalty[J]. Journal of Services marketing, 2005, 19(6): 392–400.
19. Thom R. Structural stability and morphogenesis[M]. CRC press, 2018.
20. Huang Y, Feng C. A catastrophe model for developing loyalty strategies: A case study on choice behaviour of pick-up point for online shopping [J]. International Journal of Services Operations and Informatics, 2009, 4(2): 107–22.
21. Flay B R. Catastrophe theory in social psychology: Some applications to attitudes and social behavior [J]. Behavioral Science, 1978, 23(4): 335–350.
22. Wei X, She Q. Quantitative cusp catastrophe model to explore abrupt changes in collaborative regulation behavior of e-commerce platforms[J]. Information Sciences, 2023, 642: 119127.
23. Lv S, Yang R, Huang C. Contusion and recovery of individual cognition based on catastrophe theory: a computational model[J]. Neurocomputing, 2017, 220: 210–220.
24. Hu B, Hu X. Qualitative modeling of catastrophe in group opinion[J]. Soft Computing, 2018, 22(14): 4661–4684.
25. Hu B, Du Y. Integrated analysis of employee cooperation and conflict behaviors in the context of digital technology[J]. Simulation, 2023, 99(9): 969–985.
26. Wei X, She Q. Quantitative cusp catastrophe model to explore abrupt changes in collaborative regulation behavior of e-commerce platforms[J]. Information Sciences, 2023, 642: 119127.
27. Scaringella L, Górska A, Calderon D, et al. Should we teach in hybrid mode or fully online? A theory and empirical investigation on the service–profit chain in MBAs[J]. Information & Management, 2022, 59(1): 103573.
28. Rasheed A K F, Balakrishnan J. Cutting the clutter: how minimalism drives customer citizenship behaviour within the sharing economy-based services[J]. Kybernetes, 2023.
29. Lee C T, Shen Y C, Li Z, et al. The effects of non-fungible token platform affordances on customer loyalty: A Buyer–Creator duality perspective[J]. Computers in Human Behavior, 2024, 151: 108013.
30. Silvestro R, Cross S. Applying the service profit chain in a retail environment: Challenging the "satisfaction mirror"[J]. International journal of service industry management, 2000.
31. Jiang G, Tadikamalla P R, Shang J, et al. Impacts of knowledge on online brand success: an agent-based model for online market share enhancement[J]. European Journal of Operational Research, 2016, 248(3): 1093–1103.
32. Horton J J, Chilton L B. The labor economics of paid crowdsourcing[C]//Proceedings of the 11th ACM conference on Electronic commerce. 2010: 209–218.
33. Aral S, Muchnik L, Sundararajan A. Engineering social contagions: Optimal network seeding in the presence of homophily[J]. Network Science, 2013, 1(2): 125–153.
34. Kiesling E, Günther M, Stummer C, et al. Agent-based simulation of innovation diffusion: a review[J]. Central European Journal of Operations Research, 2012, 20: 183–230.
35. Libai B, Muller E, Peres R. Decomposing the value of word-of-mouth seeding programs: Acceleration versus expansion[J]. Journal of marketing research, 2013, 50(2): 161–176.
36. Valente T W, Pumpuang P. Identifying opinion leaders to promote behavior change[J]. Health education & behavior, 2007, 34(6): 881–896.

37. Starkey F, Audrey S, Holliday J, et al. Identifying influential young people to undertake effective peer-led health promotion: the example of A Stop Smoking in Schools Trial (ASSIST)[J]. Health education research, 2009, 24(6): 977–988.
38. Watts D J, Dodds P S. Influentials, networks, and public opinion formation[J]. Journal of consumer research, 2007, 34(4): 441–458.
39. Hinz O, Skiera B, Barrot C, et al. Seeding strategies for viral marketing: An empirical comparison[J]. Journal of marketing, 2011, 75(6): 55–71.
40. Libai B, Muller E, Peres R. Decomposing the value of word-of-mouth seeding programs: Acceleration versus expansion[J]. Journal of marketing research, 2013, 50(2): 161–176.
41. Alt F, Shirazi A S, Schmidt A, et al. Location-based crowdsourcing: extending crowdsourcing to the real world[C]//Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries. 2010: 13–22.