Evolutionary food quality and location strategies for restaurants in competitive online-to-offline food ordering and delivery markets: An agent-based approach

Article *in* International Journal of Production Economics · May 2018

DOI: 10.1016/j.ijpe.2018.05.008

5 authors, including:

Zhou HE
National University of Singapore

T. C. E. Cheng
The Hong Kong Polytechnic University

Bo Fan
Shanghai Jiao Tong University

Jichang Dong
Chinese Academy of Sciences

ARTICLE IN PRESS

International Journal of Production Economics xxx (2018) 1–12

Contents lists available at ScienceDirect

International Journal of Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Evolutionary food quality and location strategies for restaurants in competitive online-to-offline food ordering and delivery markets: An agent-based approach

Zhou He [a,b], Guanghua Han [c], T.C.E. Cheng [d], Bo Fan [c], Jichang Dong [a,e,*]

[a] School of Economics and Management, University of Chinese Academy of Sciences, 80 Zhongguancun East Road, Beijing 100190, China
[b] Department of Industrial Systems Engineering and Management, National University of Singapore, 21 Lower Kent Ridge Road, Singapore 117576, Singapore
[c] School of International and Public Affairs, Shanghai Jiao Tong University, 1954 Huashan Road, Shanghai 200030, China
[d] Department of Logistics and Maritime Studies, The Hong Kong Polytechnic University, 11 Yuk Choi Road, Hong Kong, China
[e] Key Laboratory of Big Data Mining and Knowledge Management, Chinese Academy of Sciences, 80 Zhongguancun East Road, Beijing 100190, China

A R T I C L E I N F O

Keywords:
Agent-based model
Online-to-offline
Food ordering
Food delivery
Location

A B S T R A C T

In the booming online-to-offline (O2O) food ordering and delivery market, numerous independent restaurants are competing for orders placed by customers via online food ordering platforms. The food quality and location decisions are deemed to be the two principal considerations of restaurants in this emerging market. To investigate the evolutionary food quality and location behaviours of restaurants, we propose an agent-based O2O food ordering model (AOFOM) that consists of three types of agents, namely customers, restaurants, and the online food ordering platform. We explicitly model their adaptive behaviours by optimizing the agents' benefits. We find that customers' behaviours have significant impacts on the restaurants' food quality decisions. Besides, the relationship between the restaurant's location decisions and customers' waiting time is less significant in the O2O food ordering market due to the presence of an equalizing delivery service provided by the online platform. We also examine the characters of best restaurants, as well as the impacts of different delivery policies on the food quality and location decisions of restaurants.

1. Introduction

Modern information technologies and their offspring, such as computers, the Internet, smart phones, tablets, mobile applications, have fundamentally changed people's daily lives. With respect to eating, they help people work so efficiently that they almost have no time to dine out; while they also provide people with a new option: order food online, wait, receive the delivered takeaway, and eat. In such online-to-offline (O2O) transactions, the online food ordering platform services large numbers of customers and restaurants in a direct and efficient fashion, sends online orders to restaurants, and even delivers the takeaways to customers. All the three participants are able to benefit from these transactions: (1) For restaurants, this market provides a new revenue source without expanding seating capacity or wait staff. (2) For customers, this service offers a wide variety of options, ratings, reviews, and payment choices. (3) For the online platform, this business model produces a steady stream of commission. Given the above advantages, it is not surprising that the O2O food ordering and delivery market is booming. For example, China's O2O food ordering and delivery market had grown from 0.15 billion CNY in 2010 to 44.24 billion CNY in 2015, which means that the average daily increase during the six-year period was about 3 million USD.

However, from the perspective of restaurants, attracting online takeaway orders will be increasingly difficult as more rivals rush in. More importantly, unlike non-perishable products that can be delivered to distant customers, the time-sensitive nature of takeaway food limits the size of the service area. Therefore, the restaurant's sales territory covered by an online food ordering platform is bounded. For both researchers and restaurant managers, a significant question is: How should operations management (OM) of restaurants be optimized in competitive O2O food

* Corresponding author. School of Economics and Management, University of Chinese Academy of Sciences, 80 Zhongguancun East Road, Beijing 100190, China.
E-mail addresses: hezhou11b@mails.ucas.ac.cn (Z. He), hanguanghua@sjtu.edu.cn (G. Han), edwin.cheng@polyu.edu.hk (T.C.E. Cheng), fanbo@sjtu.edu.cn (B. Fan), jcdonglc@ucas.ac.cn (J. Dong).

https://doi.org/10.1016/j.ijpe.2018.05.008
Received 30 March 2017; Received in revised form 30 April 2018; Accepted 5 May 2018
Available online xxxx

Please cite this article in press as: He, Z., et al., Evolutionary food quality and location strategies for restaurants in competitive online-to-offline food ordering and delivery markets: An agent-based approach, International Journal of Production Economics (2018), https://doi.org/10.1016/j.ijpe.2018.05.008

ordering and delivery markets?

To answer this question, we first need to narrow our research scope by identifying the basic features of the market. The iResearch (2015a, b, 2016) company provides rich survey data and annual reports on China's O2O food ordering and delivery market. Combined with our observations on the market, we have the following findings: (1) The major groups of 5599 Chinese customers in 2015 were university students, senior managers, employees, and professionals. (2) When these respondents selected O2O takeaway ordering and delivery services, they mainly focused on two factors: waiting time and food quality. Defined by the survey, food quality is a broad concept including the package, temperature, taste, and ingredient quality of takeaway food. (3) The importance of food quality increased from 22.38% to 46.8% in 2016. (4) The supply chain performance of restaurants was improved by the online platforms by means of standardizing the food preparation process, improving food quality, targeting most suitable customers etc. (5) The online platforms took over the food delivery service since they have to compete with copycats by, e.g., changing from tech-heavy to asset-heavy. (6) The waiting time of customers were affected by three elements: a) the food preparing time which is often associated with food quality, b) the location of the restaurant which affects the travelling distance and time of riders, and c) the delivery policy of the online platform. (7) When scheduling dispatch riders, the resource-limited online platforms had to balance delivery cost saving against delivery performance maximizing. Based on the above findings, we suggest that food quality and location decisions are the two principal considerations of restaurants.

In this paper we aim to study the optimal decisions of independent restaurants in O2O food ordering and delivery markets. In particular, we concentrate on the following research questions:

1. What are the impacts of three possible changes on the food quality and location operations of restaurants, i.e., the increasing preference of customers for high food quality, the shortening food preparing time of the restaurant, and the different delivery policies of the online platform?
2. What are the differences between the food quality and location decisions made by the best restaurants and those made by others?

In this paper we employ the agent-based modelling (ABM) technique to create an agent-based O2O food ordering model (AOFOM) grounded in complex adaptive system (CAS) theory. In Section 2 we review three related research streams. In the AOFOM, there are three types of agents in a central business district (CBD), namely customers, restaurants, and the online food ordering platform. We explicitly model their adaptive behaviours from the perspective of optimizing the agents' benefits in Section 3. In Section 4 we consider three practical scenarios and conduct various computational experiments to observe the agents' evolutionary behaviours under them. In Section 5 we present the experimental results and highlight our research findings. Finally, we conclude the paper and suggest potential topics for future research in Section 6.

2. Literature review

In this section, we review four related research streams, namely (1) O2O, (2) competitive location models, (3) food-related operations management, and (4) agent-based modelling.

2.1. O2O

The term O2O originally means that the customer enjoys the product or service offline through buying online (Rampell, 2010). As firms have increasingly adopted the O2O approach, researchers have devoted much research attention to this topic. In general, research on the O2O approach can be divided into four streams, namely channel-related (online, offline, and integration), product/service-related (e.g., service experience), customer-related (e.g., social network), and technology-related (e.g., online recommendation).

The emergence of the online channel has brought many challenging questions to traditional production and service management, which is accustomed to the offline channel, as follows: Which channel should be selected? Why, when, and how to integrate the online and offline channels? Extensive research has been undertaken to address these questions under different scenarios. For example, Gao and Su (2016) investigated the impact of buy-online-pickup-offline on the operations of a retailer, such as disclosing real-time inventory status and reducing the hassle cost of shopping. They found that such a mode may not be suitable for all the products, but it does help retailers expand their market coverage under the proper circumstances. Zhang et al. (2017) examined when an online retailer should add an offline channel, as well as when an offline retailer should set up an online channel. They compared the retailer's profits under different channel structures and provided suggestions according to the degree of customer acceptance. To avoid channel conflicts, Choi et al. (2017) studied a specific O2O mode in the fashion industry, i.e., sell offline first, then sell online. Their analytical results under four different scenarios can be applied to deal with the trade-off between ordering cost and forecast accuracy.

There are a few studies pursuing the other three streams of O2O research. For example, Forman et al. (2009), and Kim and Krishnan (2015) found that the absence of product information (e.g., product type, price, quality) affects customers' experience and decision' on channel choice. Hsiao and Chen (2014), and Shen et al. (2017) studied customers' preference, social network, and characteristics to ascertain their impacts on customers' purchase behaviour and channel selection. Finally, research on O2O commerce from the perspective of technology includes consideration of service recommendation systems (Pan et al., 2017) and self-ordering facilities (Gao and Su, 2017).

2.2. Competitive location models

As the first study on competitive location problems, Hotelling (1929) has spurred voluminous subsequent research on this topic, which can be generally grouped into two divisions according to the competition type, i.e., static or dynamic.

Static spatial competitions are often framed as one-stage Operations Research (OR) problems (Kress and Pesch, 2012), which seek the optimal location(s) for one competitor without considering the others' reactions. A typical example is the maximum capture (MAXCAP) model proposed by ReVelle (1986). In this model, an entering firm (i.e., the follower) with several stores seeks the optimal locations to grab market share from an existing firm (i.e., the leader). The distance to the nearest store is the only factor that determines the behaviour of customers. To make the model more realistic, many components in customer behaviour have been included in subsequent studies. Drezner (1994) suggested that the attractiveness of a facility could be related to its size and service diversity. Pahlavani and Saidi-Mehrabad (2011) considered the price and location of stores, as well as the waiting time of customers. However, it is increasingly difficult for such analytical models to capture dynamic spatial interactions between facilities and customers (Drezner and Eiselt, 2002).

Players in dynamic locational competitions repeatedly re-optimize their locations in a simultaneous (such as Hotelling, 1929) or sequential (pioneered by Hakimi, 1983) manner. For instance, Plastria and Vanhaverbeke (2008) presented a leader-follower game in which the leader attempts to maximize the remaining demand after the follower's entry. They studied three classical strategies for the leader: (1) the maximin strategy, which considers the follower's location decision in the worst case; (2) the minimax regret strategy; and (3) the Stackelberg strategy where the follower also optimizes its decision. One important investigation in dynamic competition is the possible (non)existence of equilibrium situations. For example, Lu et al. (2010) developed a two-stage model with stochastic customer behaviours on networks. They searched the optimal location-price solution, and investigated the existence and uniqueness of the pure strategy Nash equilibrium. For excellent surveys on this topic, we refer the reader to Eiselt et al. (1993), and Kress and Pesch (2012). However, due to the complexity of dynamic spatial competitions with a large number of players, such models are usually very difficult to solve using game-theoretic approaches (Drezner, 2014).

2.3. Food-related operations management

From the OM viewpoint, food-related studies generally focus on the following three research strands. The first one is food quality management due to its importance to public health. Possible factors that affect food quality include quality of raw materials, selection of suppliers, control of production, and planning of distribution (Flynn et al., 1994; Ahire et al., 1996; Jayaram et al., 1999; Van der Spiegel et al., 2006). The second research strand is food supply chain management; in particular, the distribution network design. Since food products often have limited shelf lives, they require suitable temperature, humidity, and other storage conditions before arriving in kitchens, giving rise to complicated location-allocation problems for food distribution. For example, Groothedde et al. (2005) designed a large-scale collaborative hub network, where the time and cost of fast-moving transshipment can be minimized by finding the optimal hub location. Considering that the quality of perishable products deteriorates exponentially after harvest, Blackburn and Scudder (2009) optimized a hybrid supply chain in order to minimize lost value. Akkerman et al. (2010) summarized the food distribution literature concerning food quality, safety, and sustainability. The third research strand concerns service competition among food services providers. Since food catering is one of the most service-oriented industries (Merricks and Jones, 1986), existing research on the competition of restaurants falls into the category of service competition. One exception is Hwang et al. (2010), which discussed a queuing-based model to examine the optimal joint demand-capacity decision in a restaurant system under several competitive strategies. Their work, however, neglected food quality, which has been identified as one of the critical attributes for a customer in selecting a restaurant (Auty, 1992; Jack Kivela, 1997). In the context of takeaway food delivery, food quality importance increases as other factors like ambiance become relatively subordinate. Although food quality has been investigated in the food production and distribution phase, its role for restaurants in peer competition remains largely unexplored in the literature.

2.4. Agent-based modelling

An *agent* can be viewed as an abstract entity with some of the following features: autonomy, social ability, reactivity, and pro-activeness (Wooldridge and Jennings, 1995). Multiple agents form a complex adaptive system (CAS), in which each agent attempts to adapt to the changing environment by interacting with others. Holland (1996) suggested that, it is the adaptive behaviours of agents that engenders the complexity of the CAS Holland (1996). By means of agent-based modelling (ABM), the CAS theory can be applied to study various complex systems such as ecosystems, supply networks, financial markets, economies, and social systems (see, e.g., Farmer and Foley, 2009; Chandrasekaran et al., 2016).

In recent years, it has received considerable attention as a result of a growing need for tackling complex issues in market competition. For example, Sofitra et al. (2015) used ABM technique to simulate supply networks, in order to understand co-evolving relationships among interacting members (i.e., cooperation, defection, competition and co-opetition). Combined with system dynamics, heuristic algorithms, and other elements, He et al. (2013, 2014, 2016) proposed many agent-based models for the competing firms (e.g., retailers, logistics companies, service merchants), which attempt to optimize their operations (e.g., pricing, location, inventory management) in different complex markets. However, the location insights produced by these studies can hardly be applied to the O2O food ordering and delivery market, because there exists a centralized delivery service provider, i.e., the online platform.

Currently, the most similar study is He et al. (2018a), in which an empirically-grounded agent-based framework is proposed for the OM of mobile application startups. As an application of the framework, an agent-based model of China's O2O food ordering and delivery market is introduced. Although the model in He et al. (2018a) and the AOFOM in this paper have some similarities (e.g., the types of agents, simulation scenarios), there are some fundamental differences between them: (1) Different research goal and perspective. The model in He et al. (2018a) is developed to demonstrate that the proposed framework can be implemented so that the mobile application startups are able to manage the market and optimize their OM; while the AOFOM is created for the restaurants to understand how their food quality and location decisions are affected by other changes. (2) Different model assumptions and settings. Unlike He et al. (2018a) where agent locations are fixed, the restaurants in the AOFOM are moveable so that they can search for better locations in the changing market. Therefore, different assumptions (e.g.,

Table 1
Agent-related variables used in the AOFOM.

Agent[a]	Variable	Type[b]	Remark
Restaurant R_j	$q_{j,t}$	DV	Food quality, $q_{j,t} \in (0, 1)$
	$r_{j,t}$	DV	The radial coordinate
	ϕ_j	XV	The angular coordinate
	$\underline{\rho}, \overline{\rho}$	XV	The minimum and maximum takeaway preparation time
	$\rho_{j,t}$	NV	Required time to preparing takeaway food
	$b_{ij,t}$	NV	The moment that the takeaway food for customer C_i is ready for collection
	$\theta_{j,t}$	NV	Current received order count
	$\Theta_{j,t}$	NV	Accumulated received order count
Customer C_i	$R^*_{j,t}$	DV	Selected restaurant
	β	XV	Preference for food quality
	(r_i, ϕ_i)	XV	The polar coordinates
	$U_{ij,t}$, $U^*_{ij,t}$	NV	Perceived and actual utility from ordering at restaurant R_j
	$a_{ij,t}$	NV	The moment C_i places order at restaurant R_j
	$d_{ij,t}$	NV	The moment C_i receives takeaway food packaged by restaurant R_j
	$w_{ij,t}$	NV	The actual waiting duration, i.e., $d_{ij,t} - a_{ij,t}$
	$f_{ij,t}$	NV	Probability that C_i selects the takeaway food of R_j
Online platform P	α	XV	Preference for cost-saving in route planning
	V	XV	Number of riders
	s, h	XV	Rider's speed and capacity
	p	XV	Number of recent time steps to update restaurant's information
	$c_{ij,t}$	NV	The moment a dispatch rider pick-ups the takeaway food
	$l_{ij,t}$	NV	The distance between customer C_i and restaurant R_j
	$W_{ij,t}$	NV	Average waiting duration of restaurant R_j rated by customers like C_i
	$Q_{ij,t}$	NV	Average food quality of restaurant R_j
Model M	N_d, N_r	XV	Number of customers and restaurants
	Γ	XV	The duration of online ordering
	$\bar{r}$	XV	The maximum radius of the local spatial market

[a] Subscripts i, j and t are the indices of customers, restaurants, and simulation time steps, respectively.
[b] DV: decision variable; NV: endogenous variable whose value may change iteratively; XV: exogenous variable; its value remains unchanged after initialization.

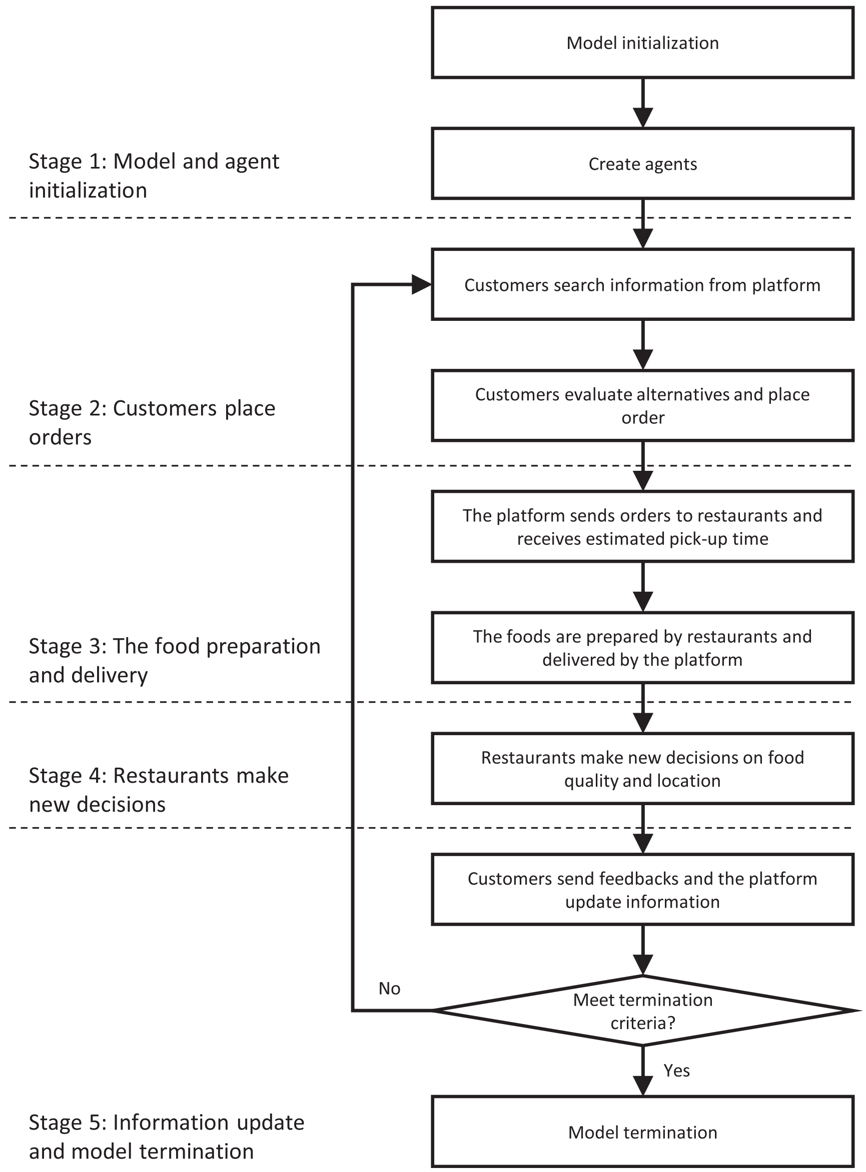

Fig. 1. The flow of the **AOFOM**, which can be generally divided into five stages.

random locations of agents and their polar coordinates) are applied in the AOFOM. (3) Different result and discussion. Due to the differences in model assumptions and settings, it is natural that the results of two models are not identical. More importantly, when discussing the results, this study focuses on restaurant-related indicators, and divides restaurants into two groups based on their order counts so that the characters of best restaurants can be recognized and discussed. In contrast, He et al. (2018a) mainly investigated how the performance of mobile application startups changes and thus ignored discussing the changes of restaurants' performance. Therefore, we suggest that this paper is the first study on the service OM of restaurants in the emerging O2O food ordering and delivery market.

3. Model description

In this section we explicitly define each agent's attributes and behaviours interacting with the other agents. Table 1 lists the agent-related variables used in the AOFOM. Fig. 1 summarizes the flow of the AOFOM, which can be generally divided into five stages: 1) model and agent initialization, 2) customers place orders, 3) the food preparation and delivery, 4) restaurants make new decisions, and 5) information update and model termination.

3.1. Stage 1: model and agent initialization

The AOFOM is composed of one online platform and multiple restaurants and customers. Except the abstract online food ordering platform, other agents are represented as discrete points and placed on a two-dimensional plane with a polar coordinate system according to their polar coordinates (r, ϕ). The pole thus can be viewed as the centre of the local spatial market, e.g., the centre of the CBD. The locations of customers are generated randomly: ϕ is uniformly distributed between $[0, 360)$ and r is determined by a truncated normal distribution that carries higher probabilities of siting customers near the pole (see Section 4.1 for details). These settings allow us to build a radial local market like a CBD or a university, where the key customers of the contemporary O2O food ordering business – employees and students – frequently place orders (iResearch, 2015b).

Unlike customers, the restaurant agents are able to relocate in order to reach the optimal location. In particular, when competing based on location, the only decision variable for a restaurant is its radial coordinate r, since the angular coordinate ϕ is exogenously specified in the AOFOM. There are two reasons for excluding ϕ in restaurants' location decision-making. The first one comes from the normally distributed demand density of a radial local market, i.e., customers gather around the pole. Compared with the angle, the radius is more meaningful as it measures the proximity to business opportunities. The other consideration is based on the delivery mechanism. For restaurants, if the platform provides the delivery service, they probably have little knowledge about the customers' exact locations, leading to fuzzy competitive location problems. Therefore, they will only consider the distance to the CBD centre when moving, i.e., either closer to or farther away from the CBD. By means of using the polar coordinate system and excluding the angular coordinate, the dimensions of location decisions can be reduced from two (i.e., longitude and latitude) to one (i.e., the radial coordinate).

3.2. Stage 2: customers place orders

As the moment at which customer C_i feels hungry is a random variable, we use $a_{ij,t}$ to represent the demand recognition moment and assume that it follows the normal distribution $N(\mu, \sigma^2)$ based on the data from Ele.me. We also observe that the lunch time often starts at 11:00 a.m. and ends at 1:30 p.m., and the peak time of placing orders is about 12:15 p.m. Therefore, if we let Γ be the duration of online ordering, i.e., $\Gamma = 150$ minutes, then the mean of the normal distribution is $\mu = \Gamma/2 = 75$. To avoid generating extreme values, we let σ be $\Gamma/6 = 25$ following the "six-sigma" principle, i.e., 99.73% of the values is contained within 3 standard deviations of the mean. Finally, we have $a_{ij,t} \sim N(75, 25^2)$. This truncated normal distribution is able to create a peak time around 12:15 p.m.

The online platform provides food quality $Q_{j,t}$ and waiting duration $W_{ij,t}$ of each restaurant. Both indicators are computed by the online platform according to historical transactions during the last P time steps. The difference is that the waiting duration $W_{ij,t}$ is related to the location of customer C_i. Therefore, the subscript i is necessary. For simplicity, each restaurant only provides one type of selectable takeaway food for all the customers. All the takeaway food types in the AOFOM are substitutable for the customers. Therefore, competition among restaurants exists.

Taking all the available information into account, customer C_i evaluates each restaurant and its food for maximizing his/her perceived utility. Since food quality and waiting duration are neither perfect substitutes nor perfect complements,[1] we use a Cobb-Douglas function to approximate the perceived utility of customer C_i at time t in a multiplicative fashion as follows:

$$U_{ij,t} = \left(\frac{W_{i,t}^{min}}{W_{ij,t}}\right)^{1-\beta} \cdot \left(\frac{Q_{j,t}}{Q_t^{max}}\right)^{\beta}, \tag{1}$$

where

$$W_{i,t}^{min} = \min\{W_{ij,t}\}_{j=1}^{N}, \tag{2}$$

$$Q_t^{max} = \max\{Q_{j,t}\}_{j=1}^{N}. \tag{3}$$

As shown in Equation (1), two attributes (i.e., waiting duration and food quality) have convex preferences, and they are re-scaled in $(0, 1]$ according to Equation (2) and Equation (3). Since people are more likely to prefer diversity in their diets because it can provide more nutrients for the human body, we assume that customer C_i chooses alternative takeaway food from restaurant R_j with the following probability:

$$f_{ij,t} = \frac{e^{U_{ij,t}}}{\sum_{j=1}^{N} e^{U_{ij,t}}}. \tag{4}$$

Equation (4), often called the *logit choice model*, denotes that "better alternatives are chosen more often" (Su, 2008). In the AOFOM, each customer orders exactly one type of takeaway food from the selected restaurant R_j^* and then waits for it.

3.3. Stage 3: the food preparation and delivery

Suppose that $\theta_{j,t}$ customers eventually select restaurant R_j at time t. The online platform immediately sends each received order to R_j, which will immediately start preparing the takeaway food on a first-in-first-out basis. In the AOFOM, we assume that all the restaurant agents are single-queuing service providers due to a lack of empirical evidence. It is also assumed that a restaurant's food preparation time ρ has a positive relationship with its quality q, which a normalized variable, i.e., $q \in (0, 1)$. In particular, $\rho \to \overline{\rho}$ as $q \to 1$. The food preparation time $\rho_{j,t}$ is static during the current time step but can vary iteratively if R_j decides to change its food quality $q_{j,t}$ in the next time step because $\rho_{j,t}$ is positively associated with $q_{j,t}$. If R_j is preparing a takeaway order, new orders will be delayed until the existing order is fulfilled. Therefore, restaurants face a trade-off between food quality and customers' waiting time.

The food dispatch task can be viewed as a dynamic vehicle routing problem with pick-ups/deliveries and time windows (VRPPDTW-D). In each time step, each customer places only one takeaway order and thus N_d dispatch jobs are created randomly. After receiving an order from customer C_i at time $a_{ij,t}$, the restaurant estimates when the takeaway food will be prepared (i.e., $b_{ij,t} \geq a_{ij,t} + \rho_{ij,t}$). The food could be collected by a rider at time $c_{ij,t} \geq b_{ij,t}$. For this delivery job, the pick-up time window at the origin (restaurant R_j's location) starts at $b_{ij,t}$, while the delivery time window is omitted. The online platform owns V homogeneous vehicles (i.e., riders) with speed s and capacity h. A rider delivers the takeaway food from its depot and finally returns to the same depot. Constrained by the rider count, speed, capacity, and the pick-up time windows, the platform's objective in the delivery process is to minimize two indicators simultaneously: (1) the maximum waiting time of all the customers, which is related to user experience and (2) the total travel distance of all the riders, which is related to cost saving. We use the exogenous variable α to weight the preference for cost saving, and convert waiting time to distance by multiplying the rider's speed s and weight it by $1 - \alpha$.

Solving VRPPDTW-D can be very time consuming since it is an *NP*-hard problem and the solution has to be revised using real-time information (Taniguchi and Shimamoto, 2004). To find optimal (or near-optimal) solutions, we develop a heuristic algorithm with the help of Ele.me, following the insertion principle proposed by Campbell and Savelsbergh (2004). We present the brief pseudo codes in Algorithm 1 and find that the algorithm yields good results for VRPPDTW-D in a relatively efficient way. Following the route produced by the algorithm, a dispatch rider picks up multiple takeaway orders at different restaurants without exceeding the capacity limit, and then delivers them to the waiting customers. For each rider, the route may change by the system when a new order is received. Therefore, the real-time delivery scheduling system has to continuously track the location and status of each rider and order so that the rider can follow the new route and all the assigned delivery jobs are fulfilled.

[1] The linear utility function is often used for perfectly substitutive attributes, i.e., some attributes can be zero or fully substituted, while the *L*-shaped utility function is often applied when the attributes are perfect complements, i.e., utility is solely determined by the lowest attribute. These two function forms are not suitable for food selection because both food quality and waiting duration are indispensable.

Algorithm 1
The insertion heuristic algorithm after receiving a new dispatch job.

```
Collect necessary information about the dispatch job (denoted by J), e.g., distance, pick-up time window, locations of the customer and restaurant;
foreach rider do
    Update current location, capacity and status of assigned dispatch jobs;
    List all the unvisited paths, e.g., path 1, path 2, ...;
    Generate all possible new plans after inserting job J, e.g., path 1, J's pick-up path, path 2, J's deliver path, ...;
    Calculate the performance of each new plan according to the objective function of the online platform;
    Find the new plan with best performance;
end
Find the rider with best performance;
Assign J to the rider and finalize its best plan;
```

3.4. Stage 4: restaurants make new decisions

In the AOFOM, customers are utility-maximizing agents and the online platform employs the above algorithm to generate the optimal delivery plan. For the restaurant R_j, its objective function is to maximize the number of received orders θ_j under two constraints: $q_j \in (0,1)$, $r_j \in (0,\bar{r})$. The challenge of tackling this optimization problem is the difficulty in mathematically expressing the final demand $\theta_{j,t}$, which is affected by the interweaving decisions of both customers and rivals, as well as the delivery plans generated by the online platform. Due to the high complexity produced by the dynamic and spatial interactions among agents, the restaurant R_j can hardly make reasonable decisions on its food quality and location.[2]

In this paper, we incorporate the estimation-and-optimization approach proposed by He et al. (2018b), which consists of two steps: (1) estimation of unknown parameters and (2) searching for the optimal decisions. First, each restaurant agent will record all its previous (food quality, radius, order count) data. Hence, in time step *t*, restaurant R_j should have $t-1$ historical records $(X_1, X_2, Y) = \{(q_{j,\tau}, r_{j,\tau}, \theta_{j,\tau})\}_{\tau=1}^{t}$ to fit the following multivariate polynomial regression model:

$$Y = z_0X_1^2X_2^2 + z_1X_1^2X_2 + z_2X_1X_2^2 + z_3X_1X_2 + z_4X_1^2 + z_5X_2^2 + z_6X_1 + z_7X_2 + z_8. \quad (5)$$

Regression model (5) basically comes from the aforementioned conclusion that "restaurants face a trade-off between food quality and customers' waiting time". Therefore, the relationship between food quality and order count is likely to be a quadratic function opening downward and the optimal food quality is within (0, 1). Similarly, it seems to be safe to assume that the relationship between radius and order count can also be described by a quadratic function. Therefore, nine parameters from z_0 to z_8 are unknown or uncertain due to inaccessible information or other agents' changing behaviours. After estimating the current parameters of the polynomial regression model using historical data, restaurant R_j obtains a specific "food quality & radius - order count" function $\theta_j(q_j, r_j)$ according to its past behaviours in dynamic competition. As simulation continues, more historical data will be collected, making the estimated results more stable and convincing. Therefore, restaurants are able to learn from the past.

Although restaurants are able to refine their decisions iteratively through estimation and optimization, there is no possibility for them to explore new options and avoid getting trapped in a local optimum. Due to the trade-off between exploitation and exploration, we employ a probabilistic mechanism to decide the mode of decision-making, i.e., randomly or optimally. Specifically, we introduce a probability $pr \in [0,1]$, which will decrease linearly with increasing time step. For example, in each time step, restaurant R_j picks a random number from the uniform distribution $U(0,1)$. If the random number is less than the current pr, R_j will choose a random decision on food quality and radius. Therefore, restaurant R_j explores the solution space at the beginning of the simulation. As pr decreases, the probability of making arbitrary decisions continues to decline since restaurant R_j has significantly investigated the possible solutions. If restaurant R_j decides to optimize its decision in time step *t*, it can estimate the unknown parameters of the regression model based on all the historical data collected, and then search for the optimal solution. Therefore, after diversifying the decisions when pr is relatively large, this probabilistic mechanism is still able to intensify the solution at the end of the simulation.

According to He et al. (2018b), the advantage of using this estimation-and-optimization approach is that it mimics the heuristic trial-and-error method, which is often used by people who have little knowledge in the problem area. Initially, the relationship between food quality, radius and order count is unknown. Hence, the restaurant agent experiments a random decision on food quality and radius, and then obtains orders from the market. As the simulation iteratively proceeds, the restaurant agent has collected sufficient information to make more reasonable decisions. Finally, the "food quality & radius - order count" function is confirmed based on the restaurant's experience and the trial-and-error process ends.

3.5. Stage 5: information update and model termination

After receiving and consuming the takeaway food, customer C_i will provide feedback on the actual waiting time C_i (i.e., $w_{ij,t} = d_{ij,t} - a_{ij,t}$, where $d_{ij,t} \geq c_{ij,t} + l_{ij,t}/s$) and the latest food quality of restaurant R_j^* (i.e., $q_{j,t}$). Based on the feedbacks, averaged food quality $Q_{j,t}$ and waiting duration $W_{ij,t}$ can be updated by the online food ordering platform. By now, all the interactions during one time step have been elaborated. Following many agent-based models, the model terminates after performing a given number of time steps.

4. Simulation

4.1. Experimental design

To validate the AOFOM in an empirical way, some real data are collected from Ele.me and other sources. We selected the Zhongguancun area (known as China's Silicon Valley) as the instance of CBD, where the employees and managers in technical and business firms are active and

[2] Some readers may argue that, in practice, a restaurant is unlikely to frequently change its location. It is true but we do not have any theoretical argument and empirical data to justify the frequency of a restaurant's location change. In fact, we have tested some cases where the restaurants change their locations in every N time steps, and found that the simulation results are similar. Therefore, we simply let $N = 1$.

Table 2
Values of exogenous parameters in the simulation experiments.

Parameter	Value	Unit	Source	Remark	Changed values under scenarios
N_d	298	–	Ele.me	Number of customers	Unchanged
N_r	7	–	Ele.me	Number of restaurants	Unchanged
Γ	150	minute	Ele.me	The online ordering duration	Unchanged
$\bar{r}$	800	meter	Ele.me	The maximum radius of the spatial market	Unchanged
β	0.47	–	iResearch (2015a)	Customers' preference for food quality	$\{0.1, 0.3, \ldots, 0.9\}$ under Scenario A
$\underline{\rho}$	1	minute	Ele.me	The minimum takeaway preparation time	Unchanged
$\overline{\rho}$	20	minute	Ele.me	The maximum takeaway preparation time	$\{10, 15, \ldots, 30\}$ under Scenario B
$r_i, r_{j,0}$	$\left\|N(0, (\bar{r}/3)^2)\right\|$	meter	–	Agents' initial radial coordinates	Unchanged
ϕ_i, ϕ_j	$U(0, 360)$	degree	–	Agents' initial angular coordinates	Unchanged
p	30	–	Ele.me	Number of recent time steps to update restaurant's information	Unchanged
V	5	–	Ele.me	Number of riders	Unchanged
s	500	meter/minute	Ele.me	Rider speed	Unchanged
h	7	–	Ele.me	Rider capacity	Unchanged
α	0.5	–	Ele.me	Preference for cost-saving in route planning	$\{0.1, 0.3, \ldots, 0.9\}$ under Scenario C

frequent customers using O2O food ordering service. We randomly selected several working days and obtained the transaction data in these days from Ele.me. We had the following findings: during the lunch time, about 2977 customers order takeaway food at 69 restaurants using Ele.me; 53 riders are involved; the average waiting time is about 40 min. Due to the extreme high computational complexity, we reduced the scale of the AOFOM to 10% by randomly removing entities. The latitude and longitude coordinates of the CBD centre are 39.9817 and 116.3099, respectively. A truncated normal distribution and a uniform distribution were used to generate the polar coordinates of the customers and restaurants, so that they were located around the CBD centre. Table 2 presents the default values of the exogenous variables in the simulation process.

To answer the research questions posed in Section 1, we design three scenarios, namely Scenario A, B and C, to examine how the market is affected by the changing behaviours of the three types of agents, namely the customers, restaurants, and online platform. We define a benchmark with the parameter settings: $\{\beta = 0.5, \overline{\rho} = 20, \alpha = 0.5\}$. Under Scenario A, $\beta \in \{0.1, 0.3, 0.7, 0.9\}$, which means the customers attach less/more importance to food quality. Under Scenario B, the maximum takeaway preparation time of restaurants $\overline{\rho}$ changes from 10 to 30 min, i.e., $\overline{\rho} \in \{10, 15, 25, 30\}$. Under Scenario C, the online platform alters its delivery policy by changing the preference for cost saving in route planning, i.e., $\alpha \in \{0.1, 0.3, 0.7, 0.9\}$. Under each scenario, only one input variable is changed, allowing us to examine to what extent the simulation results are affected by this factor.

4.2. Implementation and performance measures

We used Python to program the AOFOM and performed all the experiments on several workstations. Due to the randomness in the AOFOM (e.g., customers' probabilistic choices, restaurants' initial attempts and locations), the simulation outputs will be variable even if the inputs are the same. Hence, we performed each experiment 100 times by assigning {0, 1, …, 99} as random seeds, so that the simulation results can be well compared and reproduced. We carried out the steps presented in Fig. 1 over 360 time steps, and adopted the following indicators of restaurants in order to generate insights:

1. Average waiting time reported by customers: w_{avg}.
2. Average radius: r_{avg}.
3. Average food quality: q_{avg}.
4. Average food preparation time: ρ_{avg}.
5. Average residual sum of squares: e_{avg}.
6. Average accumulated order count: Θ_{avg}.

4.3. Verification and validation

In the verification process, we conducted extensive software testings to ensure that the model codes had no bugs and all the processes were correctly implemented. More importantly, we validated the model by evaluating the consistency between the real data and the simulation results, given the default empirical inputs as shown in Table 2. Specifically, due to data availability, we selected three indicators of restaurants for comparison: the restaurant's radius (distance to the CBD centre), food quality and its customers' average waiting time. Table 3 presents several statistic measures of both the real data and simulation results. The differences between them are small, revealing that the model has good potential to reflect the mechanism of the O2O food ordering and delivery market.

5. Results and discussion

Table 4 presents the means and standard deviations of the above indicators obtained from the 13 experiments under the three scenarios.

Table 3
Model validation results.

Indicator	Data source	Sample size[a]	Mean	STD[b]	1st quartile[c]	2nd quartile	3rd quartile
Radius of the restaurant	Real data	84	486	202.3	385	425	593
	Simulation	700	500	200.3	353	450	628
Food quality of the restaurant[d]	Real data	84	0.502	0.264	0.322	0.482	0.710
	Simulation	700	0.489	0.291	0.300	0.501	0.725
Average waiting time of the restaurant's customers	Real data	84	40.027	19.199	24.802	38.299	54.773
	Simulation	700	40.279	18.934	25.510	36.381	52.296

[a] During the 100 replications, 700 restaurant agents are created. Therefore, the sample size is 700.
[b] STD: standard deviation.
[c] The 1st, 2nd, 3rd quartiles are also known as the 25th, 50th, 75th percentiles, respectively.
[d] The food quality of real data is linearly normalized.

5.1. Scenario A

Under Scenario A, the customer's selection principle switches from "delivery efficiency first" to "food quality first" as β changes from 0 to 1. Fig. 2(c) illustrates that the average food quality of restaurants q_{avg} dramatically increases as the customers attach a greater value to this factor than delivery efficiency, revealing that customer behaviours are very powerful in shaping the O2O food ordering market. For the customers, however, the side effect is that they have to wait longer before receiving the takeaway food ordered online, since more time is required for preparation (see Fig. 2(a) and (d)).

On the restaurant's side, another important decision is the location policy in the CBD with a polar coordinates system. According to the parameter setting in Table 2, most customers are located around the CBD centre. For the restaurant, therefore, it seems that the smaller the radius (the distance to the CBD centre) is, the less delivery time the customers have to wait. Interestingly, Fig. 2(b) displays that the average radius of restaurants r_{avg} under Scenario A is about 500 m, which is relatively large since the maximum radius of the CBD is 800 m. This finding indicates that the location policy for the restaurants in the O2O food ordering market is very different from that in conventional facility location problems, i.e., "the closer, the better"; instead, due to the presence of an equalizing delivery service provided by an online ordering platform, the relationship between radius and delivery time is less significant. A piece of evidence can be found in Table 4, in which the standard deviation of average radius of restaurants r_{avg} is as large as 200 m. Besides, it can also be observed from Fig. 2(b) that r_{avg} decreases as β drops, possibly driven by the need to lessen the waiting time of customers who emphasize delivery efficiency. Therefore, the restaurants are suggested to reduce the distance to the CBD centre if the waiting time of customers matters.

We are also interested in examining what type of restaurants have greater possibility to achieve success under Scenario A. Red lines with square markers in Fig. 2 represent the best restaurants whose accumulated order counts are the largest in each experiment. Compared with other competitors, the leading restaurants are more sensitive to the change of customers' preferences, i.e., they provide higher quality takeaway food when β is high, and move towards the CBD centre for shortening the waiting time of customers when β is low. If β is extremely high or low, all restaurants suffer from greater uncertainty in decision-making, as illustrated in Fig. 2(e). In that case, however, the best restaurants will grab many more orders at the expense of its competitors, as demonstrated in Fig. 2(f). From all sub-figures in Fig. 2, we find that the best restaurants are generally more adventurous (with higher e_{avg}) and adaptive (by changing decisions on food quality and location more appropriately).

To sum up, the customers' behaviours have remarkable impacts on the restaurants' decisions and performances. The restaurants, especially the

Table 4
The means and standard deviations of the indicators under Scenarios A, B and C.

Scenario	$\{\beta, \bar{p}, \alpha\}$	Type	w_{avg}	r_{avg}	q_{avg}	ρ_{avg}	e_{avg}	Θ_{avg}
A	0.1	Best	33.0 (15.1)	493.1 (212.8)	0.382 (0.310)	7.5 (5.9)	0.812 (0.062)	15939.7 (265.3)
		Others	36.0 (17.9)	495.2 (205.5)	0.426 (0.323)	8.6 (6.1)	0.804 (0.088)	15224.6 (880.3)
		All	35.6 (17.5)	494.9 (206.5)	0.420 (0.321)	8.4 (6.1)	0.805 (0.084)	15326.7 (792.4)
	0.3	Best	34.7 (14.2)	495.9 (178.0)	0.418 (0.279)	8.3 (5.3)	0.755 (0.055)	15825.3 (173.3)
		Others	36.2 (17.7)	496.0 (210.1)	0.444 (0.341)	8.9 (6.5)	0.742 (0.061)	15243.6 (582.0)
		All	36.0 (17.2)	496.0 (205.5)	0.440 (0.332)	8.8 (6.3)	0.744 (0.060)	15326.7 (523.6)
	0.5	Best	42.7 (16.9)	499.1 (180.3)	0.560 (0.274)	11.1 (5.2)	0.737 (0.051)	15742.8 (142.7)
		Others	38.2 (18.2)	496.8 (199.8)	0.466 (0.344)	9.3 (6.5)	0.724 (0.055)	15257.4 (302.9)
		All	38.9 (18.1)	497.2 (197.2)	0.480 (0.337)	9.5 (6.4)	0.726 (0.055)	15326.7 (332.2)
	0.7	Best	53.9 (17.0)	501.5 (181.4)	0.631 (0.291)	12.4 (5.5)	0.757 (0.056)	16030.2 (296.5)
		Others	44.6 (17.3)	498.4 (198.2)	0.582 (0.352)	11.5 (6.7)	0.727 (0.057)	15209.5 (264.9)
		All	45.9 (17.3)	498.8 (195.8)	0.589 (0.343)	11.6 (6.5)	0.731 (0.057)	15326.7 (269.4)
	0.9	Best	53.9 (17.7)	503.4 (205.3)	0.693 (0.314)	13.7 (6.0)	0.806 (0.074)	16420.3 (546.7)
		Others	46.9 (15.7)	500.2 (200.6)	0.646 (0.342)	12.7 (6.5)	0.751 (0.064)	15144.5 (477.1)
		All	47.9 (16.0)	500.7 (201.3)	0.653 (0.338)	12.8 (6.4)	0.759 (0.065)	15326.7 (487.0)
B	10	Best	18.8 (5.4)	501.8 (190.3)	0.574 (0.285)	5.9 (2.6)	0.741 (0.048)	15781.8 (147.6)
		Others	17.8 (6.4)	497.8 (205.0)	0.474 (0.353)	5.0 (3.2)	0.723 (0.056)	15250.9 (327.6)
		All	17.9 (6.3)	498.3 (203.0)	0.489 (0.346)	5.1 (3.1)	0.725 (0.055)	15326.7 (360.0)
	15	Best	32.3 (11.6)	500.2 (200.4)	0.614 (0.256)	9.2 (3.6)	0.739 (0.048)	15773.7 (150.5)
		Others	27.7 (12.0)	497.9 (202.9)	0.460 (0.360)	7.0 (5.0)	0.725 (0.055)	15252.3 (304.7)
		All	28.3 (12.1)	498.2 (202.6)	0.482 (0.352)	7.3 (4.9)	0.727 (0.055)	15326.7 (340.7)
	20	Best	42.7 (16.9)	499.1 (180.3)	0.560 (0.274)	11.1 (5.2)	0.737 (0.051)	15742.8 (142.7)
		Others	38.2 (18.2)	496.8 (199.8)	0.466 (0.344)	9.3 (6.5)	0.724 (0.055)	15257.4 (302.9)
		All	38.9 (18.1)	497.2 (197.2)	0.480 (0.337)	9.5 (6.4)	0.726 (0.055)	15326.7 (332.2)
	25	Best	62.6 (23.6)	494.0 (176.2)	0.580 (0.306)	14.2 (7.3)	0.740 (0.047)	15772.0 (131.0)
		Others	51.0 (24.1)	496.6 (191.1)	0.455 (0.357)	11.2 (8.6)	0.723 (0.057)	15252.5 (325.2)
		All	52.7 (24.3)	496.2 (189.1)	0.473 (0.353)	11.6 (8.5)	0.726 (0.056)	15326.7 (355.2)
	30	Best	81.1 (31.1)	488.1 (179.5)	0.626 (0.295)	18.3 (8.6)	0.739 (0.054)	15749.9 (138.0)
		Others	65.1 (30.8)	496.3 (202.0)	0.465 (0.345)	13.6 (10.0)	0.725 (0.056)	15256.2 (317.2)
		All	67.4 (31.3)	495.1 (198.9)	0.488 (0.343)	14.3 (10.0)	0.727 (0.056)	15326.7 (344.7)
C	0.1	Best	35.6 (8.5)	498.5 (193.8)	0.579 (0.270)	11.4 (5.1)	0.735 (0.051)	15773.0 (159.5)
		Others	35.2 (11.5)	495.3 (196.9)	0.451 (0.358)	9.0 (6.8)	0.725 (0.056)	15252.4 (302.6)
		All	35.3 (11.1)	495.7 (196.4)	0.469 (0.349)	9.3 (6.6)	0.726 (0.056)	15326.7 (339.6)
	0.3	Best	38.8 (12.5)	499.7 (186.1)	0.592 (0.259)	11.7 (4.9)	0.736 (0.056)	15759.6 (159.6)
		Others	38.1 (15.1)	498.4 (198.4)	0.462 (0.353)	9.2 (6.7)	0.725 (0.056)	15254.6 (307.2)
		All	38.2 (14.7)	498.6 (196.7)	0.481 (0.344)	9.6 (6.5)	0.727 (0.056)	15326.7 (340.3)
	0.5	Best	42.7 (16.9)	499.1 (180.3)	0.560 (0.274)	11.1 (5.2)	0.737 (0.051)	15742.8 (142.7)
		Others	38.2 (18.2)	496.8 (199.8)	0.466 (0.344)	9.3 (6.5)	0.724 (0.055)	15257.4 (302.9)
		All	38.9 (18.1)	497.2 (197.2)	0.480 (0.337)	9.5 (6.4)	0.726 (0.055)	15326.7 (332.2)
	0.7	Best	46.0 (16.2)	492.4 (169.6)	0.616 (0.282)	12.1 (5.4)	0.738 (0.052)	15758.7 (133.0)
		Others	44.0 (18.1)	495.5 (196.6)	0.461 (0.350)	9.2 (6.7)	0.724 (0.056)	15254.7 (308.1)
		All	44.2 (17.9)	495.1 (193.0)	0.483 (0.346)	9.6 (6.6)	0.726 (0.056)	15326.7 (339.1)
	0.9	Best	49.7 (19.2)	484.4 (203.4)	0.626 (0.268)	12.3 (5.1)	0.737 (0.049)	15783.9 (150.5)
		Others	56.3 (19.5)	491.9 (195.5)	0.447 (0.347)	8.9 (6.6)	0.727 (0.057)	15250.6 (322.9)
		All	55.4 (19.6)	490.8 (196.7)	0.472 (0.342)	9.4 (6.5)	0.729 (0.056)	15326.7 (357.0)

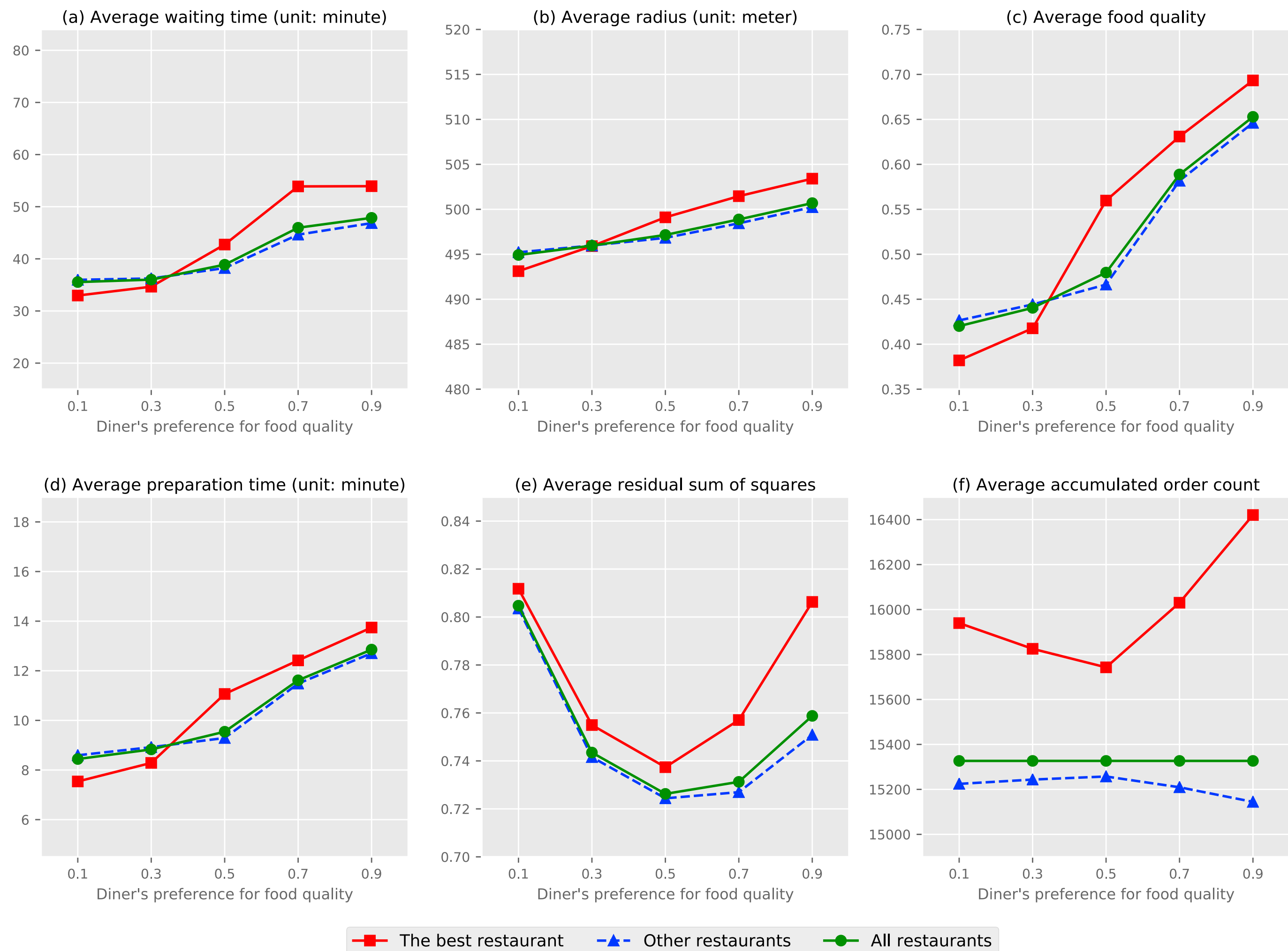

Fig. 2. Experimental results under Scenarios A.

leading ones, adjust their food quality decisions to better follow the changes of customers' preferences. The relationship between radius and delivery time is less significant in the O2O food ordering market since the impact of location decisions on customers' waiting time is largely replaced by the delivery efficiency of the online platform.

5.2. Scenario B

Scenario B assumes that all the restaurants invest more in the O2O food ordering business, and thus the food preparation efficiency is improved. Under this scenario, less time is required to prepare the takeaway food at the same quality. Since the customers' preference is not changed, the restaurants barely adjust their food quality decisions (see Fig. 3(c)). Therefore, the average preparation time decreases almost linearly, as demonstrated in Fig. 3(d).

Other findings under Scenario B are very similar to those we obtained under Scenario A: (1) The best restaurants have greater residual sum of squares, implying that they have explored many food quality and location decisions and experienced higher uncertainty in decision-making (see Fig. 3(e)). (2) The best restaurants maintain their competitive advantage by providing higher quality takeaway food, although this policy yields longer preparation time under Scenario B. (3) Fig. 3(b) shows that the change of the restaurants' location decisions is relatively small. However, the best restaurants, whose food preparation time is higher, are still active in moving towards to the CBD centre for reducing the waiting time of customers. Combined with the findings under Scenario A, we suggest that the conventional location principle (i.e., “the closer, the better”) could be useful when reducing waiting time becomes important, although it is still unnecessary for the restaurants to locate at the CBD centre since the online platform is evening the customers' waiting time out.

To conclude, the efficiency improvement in the food preparation process has little impact on the restaurant's food quality decisions. Compared with rivals, the best restaurants are still characterized by having higher food quality, greater uncertainty in decision-making, and larger possibility of finding that the conventional location principle (i.e., “the closer, the better”) could be useful when reducing waiting time becomes important.

5.3. Scenario C

When planning new routes for all the dispatch riders, the online platform considers two factors, namely reducing the maximum waiting time of customers and lessening the average travel distance of riders. Under Scenario C, the platform may concentrate on the first factor (i.e., α declines), or the second factor (i.e., α increases). We find that the changes of delivery policy can hardly affect the restaurants' decisions on food quality, as shown in Fig. 4(c). However, the average radius of restaurants has different trends when the delivery policy changes. In particular, when the online platform attempts to minimizing the maximum waiting time of customers (i.e., α declines), the restaurants are inattentive to the initiative and thus they do not change their decisions. Therefore, it is the

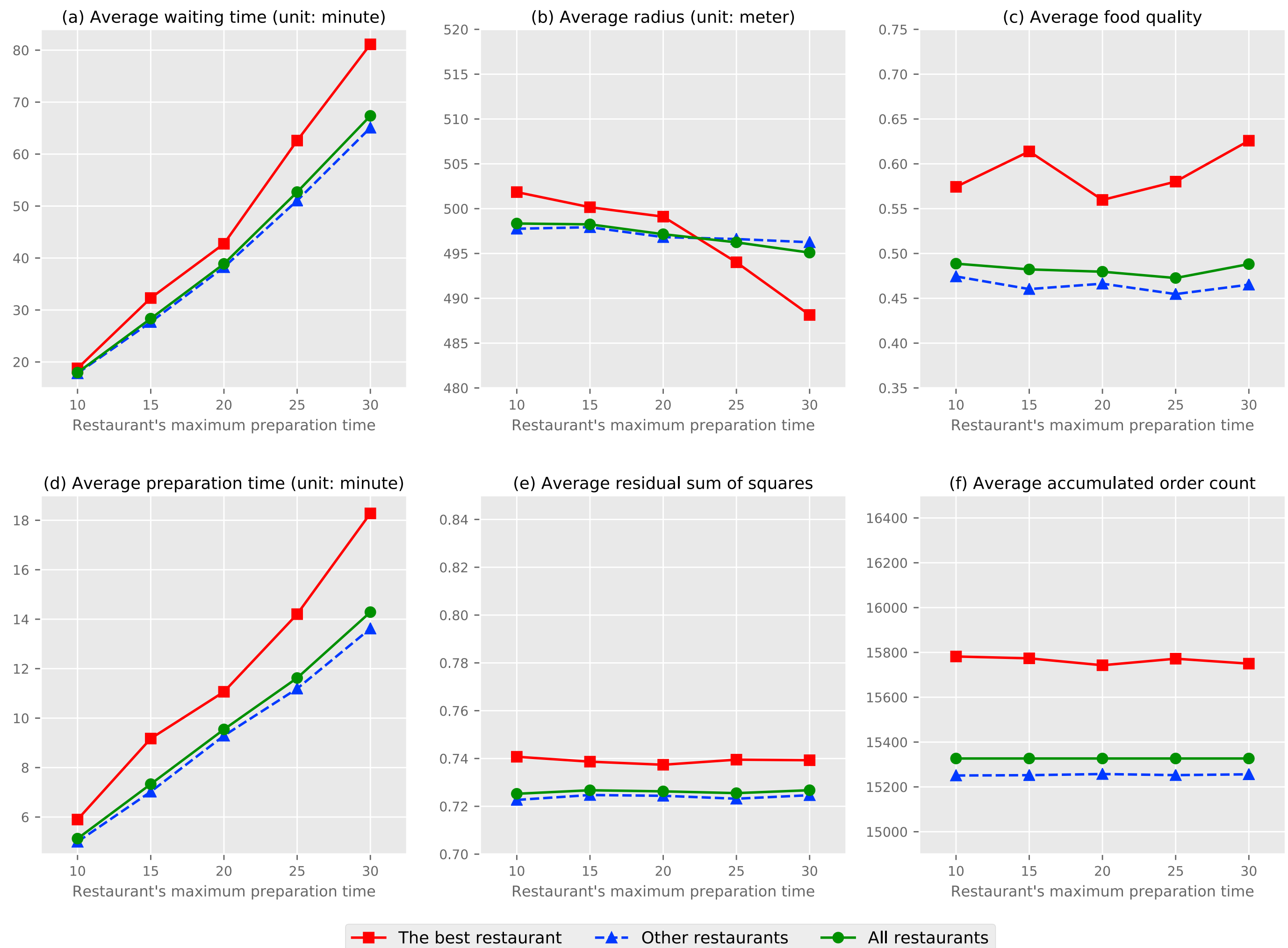

Fig. 3. Experimental results under Scenarios B.

online platform that reduces the w_{avg}, as well as its standard deviation (see Table 4). On the other hand, the costing-saving online platform tends to minimize the travel distance of riders, making it important for the restaurants to relocate to the central part of the CBD. Therefore, we find that the average waiting time of customers increases in Fig. 4(a), and the average radius of restaurants declines in Fig. 4(b).

To recap, the restaurants' food quality decisions mainly depend on the customers' preference, rather than the changes from the restaurant or the online platform. However, the delivery policy determined by the online platform is able to affect the customers' waiting time, as well as the restaurant's location decisions.

6. Conclusions

In this paper we propose an agent-based O2O food ordering model (AOFOM) to investigate the evolutionary food quality and location behaviours of independent restaurants in this emerging market. The AOFOM consists of three types of agents in a central business district: (1) Customer agents follow the classical decision-making process to select their most favourite restaurants that offer high utility based on their own preferences and the online menus. (2) Restaurant agents provide takeaway food and pursue suitable food quality and location strategies using an estimation-and-optimization mechanism. (3) The online food ordering platform agent collects comprehensive information in the market, dispatches all takeaway food orders for the restaurant agents, and attempts to ensure that each customer receives his/her takeaway order in a reasonable time by solving a VRPPDTW-D. We derive the optimal behaviours of restaurants in response to competition and evolution of the AOFOM.

After verifying and validating the AOFOM empirically, we conduct 13 experiments with 100 replications each under three scenarios. Based on the simulation results, we answer the research questions posed in the Introduction Section as follows:

1. If customers prefer higher food quality, the restaurants will increase their food quality levels accordingly. The restaurants, especially the leading ones, will adjust their food quality decisions to better follow the changes of customers' preferences. Hence, customers' behaviours have significant impacts on the restaurants' food quality decisions.
2. If the food preparing efficiency is improved, the restaurant's food quality will not be significantly affected because it is mainly based on customers' choices. Compared with the rivals, the best restaurants are more likely to follow the conventional location principle, i.e., “the closer, the better”, which could be useful when reducing waiting time becomes important.
3. If the delivery policy is changed by the online platform, the customers' waiting time, as well as the restaurant's location decisions, will be greatly affected. Therefore, the online platform plays an important role in market performance.
4. The best restaurants are generally characterized by having higher food quality and greater uncertainty in decision-making.

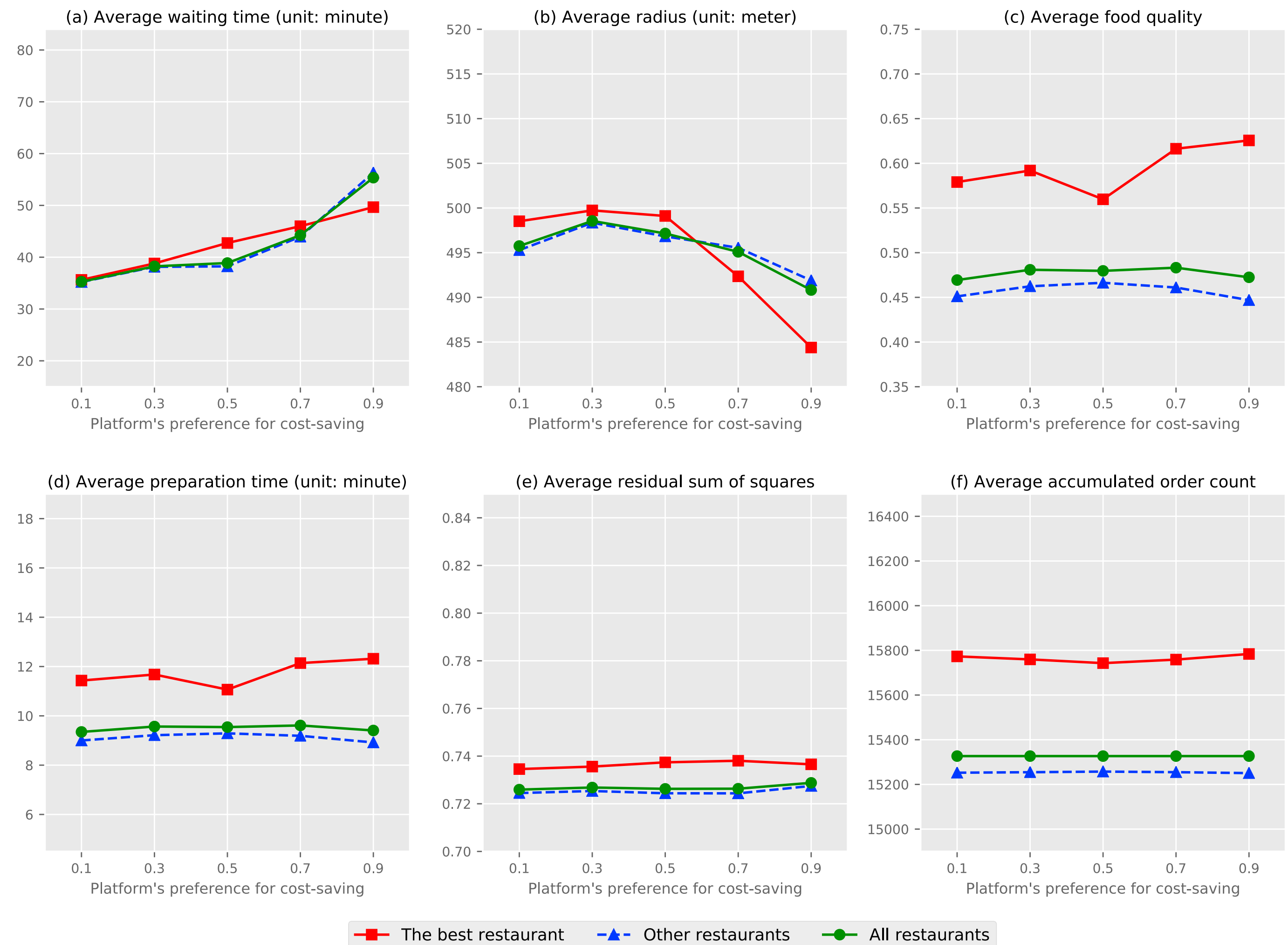

Fig. 4. Experimental results under Scenarios C.

Our study advances previous research in several aspects. (1) To the best of our knowledge, this paper is the first study on the service OM of restaurants in the emerging O2O food ordering and delivery market. Therefore, our findings offer timely and meaningful insights on the food quality and location strategies for numerous independent restaurants. (2) We employ the agent-based modelling technique to model the market, rather than mathematical approaches. Therefore, the complex, dynamic and non-linear interactions among agents can be well captured. (3) Based on the accumulated order count, we divide all restaurants into two groups (the best ones and others), and analyse the differences of their decisions to understand what strategies are more likely to help restaurants succeed in competition.

We suggest several directions for future research. First, price, minimum order quantity, and other elements neglected in our model can be taken into account in an extended version of the AOFOM, which would make agents' behaviours much more realistic. Second, deeper research on the operations management of the online food ordering platform could be interesting and necessary as it plays an important role in the market. Finally, it is worth collecting and using individual-level behavioural information and other empirical data for further agent-based studies on the O2O food ordering and delivery market.

Acknowledgement

Han was supported in part by the National Natural Science Foundation of China (No. 71501128, 71632008). Cheng was supported in part by The Hong Kong Polytechnic University under the Fung Yiu King - Wing Hang Bank Endowed Professorship in Business Administration. Fan was supported in part by the National Key Research and Development Program of China (No. 2006YEF0122300), National Natural Science Foundation of China (No. 71371122), National Social Science Foundation of China (No. 14ZDB152), and Inter-discipline Foundation of Shanghai Jiao Tong University (No. 16JXZD02). Dong was supported in part by the National Natural Science Foundation of China (No. 71573244, 71532013 and 71403260). The authors acknowledge Mr. Mengyun Xu and his team in Ele.me for providing useful data and suggestions.

References

Ahire, S.L., Golhar, D.Y., Waller, M.A., 1996. Development and validation of TQM implementation constructs. Decis. Sci. J. 27, 23–56.

Akkerman, R., Farahani, P., Grunow, M., 2010. Quality, safety and sustainability in food distribution: a review of quantitative operations management approaches and challenges. Spectrum 32, 863–904.

Auty, S., 1992. Consumer choice and segmentation in the restaurant industry. Serv. Ind. J. 12, 324–339.

Blackburn, J., Scudder, G., 2009. Supply chain strategies for perishable products: the case of fresh produce. Prod. Oper. Manag. 18, 129–137.

Campbell, A.M., Savelsbergh, M., 2004. Efficient insertion heuristics for vehicle routing and scheduling problems. Transport. Sci. 38, 369–378.

Chandrasekaran, A., Linderman, K., Sting, F.J., Benner, M.J., 2016. Managing R&D project shifts in high-tech organizations: a multi-method study. Prod. Oper. Manag. 25, 390–416.

Choi, T.M., Chen, Y., Chung, S.H., 2017. Online-offline fashion franchising supply chains without channel conflicts: choices on postponement and contracts. Int. J. Prod. Econ. https://doi.org/10.1016/j.ijpe.2017.05.006.

Drezner, T., 1994. Locating a single new facility among existing unequally attractive facilities. J. Reg. Sci. 34, 237–252.
Drezner, T., 2014. A review of competitive facility location in the plane. Log. Res. 7, 1–12.
Drezner, T., Eiselt, H.A., 2002. Consumers in competitive location models. In: Drezner, Z., Hamacher, H.W. (Eds.), Facility Location: Applications and Theory. Springer, pp. 151–178 chapter 5.
Eiselt, H.A., Laporte, G., Thisse, J.F., 1993. Competitive location models: a framework and bibliography. Transport. Sci. 27, 44–54.
Farmer, J.D., Foley, D., 2009. The economy needs agent-based modelling. Nature 460, 685–686.
Flynn, B.B., Schroeder, R.G., Sakakibara, S., 1994. A framework for quality management research and an associated measurement instrument. J. Oper. Manag. 11, 339–366.
Forman, C., Ghose, A., Goldfarb, A., 2009. Competition between local and electronic markets: how the benefit of buying online depends on where you live. Manag. Sci. 55, 47–57.
Gao, F., Su, X., 2016. Omnichannel retail operations with buy-online-and-pick-up-in-store. Manag. Sci. 63, 2478–2492.
Gao, F., Su, X., 2017. Omnichannel service operations with online and offline self-order technologies. Manag. Sci. http://doi.org/10.1287/mnsc.2017.2787.
Groothedde, B., Ruijgrok, C., Tavasszy, L., 2005. Towards collaborative, intermodal hub networks: a case study in the fast moving consumer goods market. Transport. Res. E Logist. Transport. Rev. 41, 567–583.
Hakimi, S.L., 1983. On locating new facilities in a competitive environment. Eur. J. Oper. Res. 12, 29–35.
He, Z., Cheng, T.C.E., Dong, J., Wang, S., 2014. Evolutionary location and pricing strategies in competitive hierarchical distribution systems: a spatial agent-based model. IEEE Trans. Syst. Man Cybern.: Syst. 44, 822–833.
He, Z., Cheng, T.C.E., Dong, J., Wang, S., 2016. Evolutionary location and pricing strategies for service merchants in competitive O2O markets. Eur. J. Oper. Res. 254, 595–609.
He, Z., Fan, B., Cheng, T.C.E., 2018a. Managing emerging service markets created by mobile application startups: An empirically-grounded agent-based framework for operations management. Working paper.
He, Z., Luo, C., Tan, C.H., Wu, H., Fan, B., 2018b. Simulating an agent's decision-making process in black-box managerial environment: an estimation-and-optimisation approach. J. Simulat. https://doi.org/10.1080/17477778.2018.1440946.
He, Z., Wang, S., Cheng, T.C.E., 2013. Competition and evolution in multi-product supply chains: an agent-based retailer model. Int. J. Prod. Econ. 146, 325–336.
Holland, J., 1996. Hidden Order: How Adaptation Builds Complexity. Addison-Wesley.
Hotelling, H., 1929. Stability in competition. Econ. J. 39, 41–57.
Hsiao, L., Chen, Y.J., 2014. Strategic motive for introducing Internet channels in a supply chain. Prod. Oper. Manag. 23, 36–47.
Hwang, J., Gao, L., Jang, W., 2010. Joint demand and capacity management in a restaurant system. Eur. J. Oper. Res. 207, 465–472.
iResearch, 2015a. 2015 Report of China's O2O Food Delivery Customers. http://report.iresearch.cn/report/201506/2396.shtml. (Accessed 29 April 2018) (In Chinese).
iResearch, 2015b. 2015 Report of China's O2O Food Delivery Industry. http://report.iresearch.cn/report/201504/2370.shtml. (Accessed 29 April 2018) (In Chinese).
iResearch, 2016. 2016 Report of China's O2O Food Delivery Industry. http://report.iresearch.cn/report/201607/2615.shtml. (Accessed 29 April 2018) (In Chinese).
Jack Kivela, J., 1997. Restaurant marketing: selection and segmentation in Hong Kong. Int. J. Contemp. Hospit. Manag. 9, 116–123.
Jayaram, J., Droge, C., Vickery, S.K., 1999. The impact of human resource management practices on manufacturing performance. J. Oper. Manag. 18, 1–20.
Kim, Y., Krishnan, R., 2015. On product-level uncertainty and online purchase behavior: an empirical analysis. Manag. Sci. 61, 2449–2467.
Kress, D., Pesch, E., 2012. Sequential competitive location on networks. Eur. J. Oper. Res. 217, 483–499.
Lu, X., Li, J., Yang, F., 2010. Analyses of location-price game on networks with stochastic customer behavior and its heuristic algorithm. J. Syst. Sci. Complex. 23, 701–714.
Merricks, P., Jones, P., 1986. The Management of Catering Operations. Rinehart and Winston, Holt.
Pahlavani, A., Saidi-Mehrabad, M., 2011. A competitive facility location model with elastic demand and patronising behaviour sensitive to location, price and waiting time. Int. J. Logist. Syst. Manag. 10, 293–312.
Pan, Y., Wu, D., Olson, D.L., 2017. Online to offline (O2O) service recommendation method based on multi-dimensional similarity measurement. Decis. Support Syst. 103, 1–8.
Plastria, F., Vanhaverbeke, L., 2008. Discrete models for competitive location with foresight. Comput. Oper. Res. 35, 683–700.
Rampell, A., 2010. Why Online to Offline Commerce Is a Trillion Dollar Opportunity. (Accessed 30 April 2018).
ReVelle, C., 1986. The maximum capture or "Sphere of Influence" location problem: Hotelling revisited on a network. J. Reg. Sci. 26, 343–358.
Shen, B., Qian, R., Choi, T.M., 2017. Selling luxury fashion online with social influences considerations: demand changes and supply chain coordination. Int. J. Prod. Econ. 185, 89–99.
Sofitra, M., Takahashi, K., Morikawa, K., 2015. The coevolution of interconnected relationship strategies in supply networks. Int. J. Prod. Res. 53, 6919–6936.
Van der Spiegel, M., Luning, P., De Boer, W., Ziggers, G., Jongen, W., 2006. Measuring effectiveness of food quality management in the bakery sector. Total Qual. Manag. Bus. Excel. 17, 691–708.
Su, X., 2008. Bounded rationality in newsvendor models. Manuf. Serv. Oper. Manag. 10, 566–589.
Taniguchi, E., Shimamoto, H., 2004. Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. Transport. Res. C Emerg. Technol. 12, 235–250.
Wooldridge, M., Jennings, N.R., 1995. Intelligent agents: theory and practice. Knowl. Eng. Rev. 10, 115–152.
Zhang, P., He, Y., Shi, C.V., 2017. Retailer's channel structure choice: online channel, offline channel, or dual channels? Int. J. Prod. Econ. 191, 37–50.