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# Evolutionary location and pricing strategies for service merchants in competitive O2O markets

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ABSTRACT

Attracting customers in the online-to-offline (O2O) business is increasingly difficult as more competitors are entering the O2O market. To create and maintain sustainable competitive advantage in crowded O2O markets requires optimizing the joint pricing-location decision and understanding customers' behaviours. To investigate the evolutionary location and pricing behaviors of service merchants, this paper proposes an agent-based competitive O2O model in which the service merchants are modeled as profit-maximizing agents and customers as utility-maximizing agents that are connected by social networks through which they can share their service experiences by word of mouth (WOM). It is observed that the service merchant should standardize its service management to offer a stable expectation to customers if their WOM can be ignored. On the other hand, when facing more socialized customers, firms with variable service quality should adopt aggressive pricing and location strategies. Although customers' social learning facilitates the diversity of services in O2O markets, their online herd behaviors would lead to unpredictable offline demand variations, which consequently pose performance risk to the service merchants.



## 1. Introduction

Modern information technologies (IT) and their offspring, such as the Internet, smart phones, mobile APPs, have thoroughly changed the way people find and share information. Thanks to business globalization and the existence of international supply networks, consumers can virtually purchase any product from any corner of the world as long as consumers have its information. With the evolution and proliferation of online shopping, new physical items for online sale have become less standardized. A good example is *Amazon.com*, which started as an online book store, later adding diversified products (e.g., DVDs, toys, consumer electronics etc.), and now selling many non-standardized commodities (e.g., clothing, shoes, jewellery etc).

What is the next to sell online? The most possible answer is service, which generally has the following characteristics: intangibility, heterogeneity, inseparability, and perishability (Lovelock & Gummesson, 2004; Moeller, 2010; Pride & Ferrell, 2014). A case in point is that many firms in China, both big and small, are endeavouring to enter the online-to-offline (O2O) business, which is believed to be the biggest pie in e-commerce (Reuters, 2014). According to Rampell (2010), who first coined the term, O2O commerce aims to "find customers online and bring them into real-world stores". From the perspective of service providers, however, attracting customers in the O2O market is increasingly difficult as more rivals are rushing in. *Groupon.com*, a world-wide company providing group-buying information and coupons for local service deals, reported that it retained about 950,000 featured merchants by the end of 2014, a remarkable increase of 46% over 2013 (Groupon, 2015). Such a phenomenal growth rate illustrates the rapid development of O2O commerce, but also raises a significant question to both researchers and service merchants: How to optimize service management to create and maintain sustainable competitive advantage in the crowded O2O market?

It is very difficult to answer this question directly, since service management consists of a multitude of operations in practice. The existing service marketing literature could help us to identify the most important decision variables in the context of the O2O business. The service marketing mix has been extended from the traditional "four P's" (McCarthy, 1960) to the "seven P's"

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(Booms & Bitner, 1981) whereby *people*, *physical evidence*, and *process* are added to the original *product*, *place*, *promotion*, and *price*. These elements in the marketing mix, however, vary significantly in importance for different types of products/services (Kurtz & Boone, 1987). Therefore, the research scope of this paper is narrowed by observing some real O2O cases. As found from *Groupon*'s website, it generally provides the following information on a local deal to customers: service description, price, merchant location(s), and reviews from experienced customers, revealing that these features are the basic and key aspects for capturing online business opportunities in today's O2O market. In terms of service management, the four features can be generally categorized into two competitive factors.

The first competitive factor comprises competitive pricing and location strategies. In response to competition, profit-maximizing service firms may change their pricing strategies in the short term to attract more consumers, or change their locations in the long term to reduce transport cost and offer more efficient services to customers (He, Cheng, Dong, & Wang, 2014). It is worth noting that, this paper only focuses on medium-sized merchants with multiple physical stores. The reasons for this choice are as follows: (1) Most services cannot be delivered to customers who are too far away. In other words, the service coverage of a physical store is bounded by the farthest distance that customers can accept. To vie for the demands distributed throughout a city-wide region, opening more stores may be the most effective way to gain market share. (2) Unlike large companies that have gained market dominance, medium-sized firms are more pressed by peer competition. (3) The findings observed in this paper are applicable to the case with small-sized merchants by reducing the number of stores. In view of the above considerations, this work is able to provide timely and meaningful insights concerning the joint pricing-location decision for numerous small- and medium-sized service merchants that have to or tend to participate in the highly competitive O2O market.

The second competitive factor embraces customer's behavior and words-of-mouth (WOM). Customers play an increasingly important role in service management in the contemporary IT era due to the following reasons: (1) Customers are not only the ones who purchase services and provide reviews, but also the service co-producers or co-creators of value (Vargo & Lusch, 2008). Most modern products are manufactured by assembly line robots, which are powerful to control product quality precisely. In contrast, service quality, which contains many features that cannot be objectively measured (Fitzsimmons & Fitzsimmons, 2011), is variable due to the heterogeneities in employees' skills, customers' needs, and employee-customer interactions (Edvardsson, Gustafsson, & Roos, 2005). (2) The variability of service quality could lead to a difference between customer perception and expectation. According to the classical service quality gap model (Parasuraman, Zeithaml, & Berry, 1985), the various forms of difference between customer perception and expectation determine customer satisfaction and consequently WOM of customers (Zeithaml, Berry, & Parasuraman, 1996). (3) Customers are increasingly encouraged to share their WOM on services via social networks. For example, *LivingSocial.com*, another popular O2O platform, offers a customer a free deal if three of his/her friends purchase the same deal by clicking his/her referral link (Livingsocial, 2015). From *Facebook.com* and *Twitter.com*, it can be observed that people share their WOM of their service experiences with one another in a spontaneous manner. (4) Many studies (see, e.g., Glynn Mangold, Miller, & Brockway, 1999; Berger, 2014) have shown that WOM has a powerful impact on customers' purchasing behavior as it reduces their perceived risk of service quality before purchase (Ennew, Banerjee, & Li, 2000; File, Cermak, & Prince, 1994). (5) The cost for customers to gather service information has dramatically decreased, which allows customers to more conveniently find and evaluate substitute services on online storefronts. For instance, when browsing some interested deals on *Groupon*, it will automatically recommend deals based on your location and personal preferences. Facing these challenges from competitors and clients, managers are keen to understand how to adapt to and co-evolve with the changing behaviors of online customers.

This paper aims to study the optimal decisions of multi-store service firms in response to increasingly fierce O2O competition and more socialized customer behavior. The authors attempt to shed light on the following challenging research and practical issues for service management:

1. What are the optimal pricing and location strategies for profit-maximizing service firms in competitive O2O markets?
2. What are the impacts of more socialized customer behavior on the above strategies?

This paper employs the technique of agent-based modeling (ABM) to create an agent-based competitive O2O model (ACOM). Section 2 introduces ABM and provides three reasons for choosing ABM to simulate competitive O2O markets. In the ACOM, the service merchants are modeled as profit-maximizing agents and customers as utility-maximizing agents that are connected by social networks through which they can share their service experiences by WOM. All the agents' decision-making processes are carefully modeled from the perspective of optimization in Section 3. In Section 4 the authors design two scenarios and conduct many computational experiments. Section 5 presents the experimental results and discuss the findings. Finally, Section 6 concludes the paper and suggest potential topics for future research.

This study advances previous works in several aspects. First, existing studies are extended by developing a promising framework for modeling individual agents' optimal behaviors in competitive O2O markets. In addition, the authors consider not only firms' evolutionary pricing and location strategies, but also consumers' behaviors that are often neglected in traditional Operations Research (OR) modeling research. Moreover, the findings are obtained from the micro interactions among the agents throughout the evolution of the ACOM, which provide service merchants with valuable and practical managerial insights to gain a competitive edge in competitive O2O markets.

## 2. Literature review

The literature is reviewed based on three related research streams, namely (1) competitive location and pricing decisions, (2) word of mouth, and (3) agent-based modeling. Since each research stream contains a large body of literature, the authors only survey the studies that are most relevant to this research for the sake of conciseness.

### 2.1. Competitive location and pricing decisions

Research on spatial analysis of competing firms in the business context began with a well-known paper by Hotelling (1929), which studied the siting of vendors on a beach, under the assumption that customers are uniformly distributed in a linear market and they patronize the closest vendor. He found that, given two vendors, both of them choose to locate in the middle of the beach, known as the "main street" effect. Serra and ReVelle (1999) extended the work to the case with a network and proposed the competitive location and pricing problem (PMAXCAP), where an entering retail firm with several stores seeks both optimal location and pricing decisions to compete against an existing firm. The customer's decision on patronizing a store depends not only on location (transportation cost) but also on price (purchase cost). Since it is a NP-hard problem, they developed a heuristic algorithm combined with tabu search to solve the simplest form of PMAXCAP. A shortcoming of this classical model is that it neglects the response of the existing firm when optimizing the entering firm's decisions. Several extensions of PMAXCAP have been developed to adapt to different scenarios by changing or relaxing some assumptions. For example, the mill pricing policy was compared with delivered pricing (Pelegrín, Fernández, Suárez, & García, 2006) and discriminatory pricing (Fernández, Pelegrín, Pérez, & Peeters, 2007) to examine the impacts of spatial pricing on the Nash equilibria of the optimal price and location.

There is a remarkable trend in this field. Some models focus on other important components, especially customer characteristics and facility attributes (Drezner & Eiselt, 2002), and spatial customer behaviors reacting to firms. For example, attractiveness, also often called utility, has been used to measure the positive attraction a customer feels for a facility in a precise way. Lu, Li, and Yang (2010) introduced stochastic customer behavior in networks to a two-stage model to find the expected market share. A specified utility function has been adopted to investigate the pure strategy Nash equilibrium price based on tabu search. Pahlavani and Saidi-Mehrabad (2011) developed a new paradigm to formulate customer's patronizing behavior, which is modeled as a probability distribution perceived according to price, location, and waiting time. Küçükaydin, Aras, and Altinel (2012) presented a leader-follower game with adjustable attractiveness levels. The profit-maximizing firms in this game are able to open new stores and close existing ones in response to competition. The competitive location and pricing problem may be extended to more sophisticated cases where additional factors of realistic customer and firm behaviors are considered, e.g., foresight (Plastria & Vanhaverbeke, 2008), risk management (Wagner, Bhadury, & Peng, 2009), and hierarchical location (Şahin & Süral, 2007). Although such analytical models can yield optimal solutions via mathematical analysis, they are often limited in their ability in capturing the spatial interactions between all the participants in the presence of competition (Drezner & Eiselt, 2002).

### 2.2. Word of mouth

Arndt (1967, p. 190) was the first to formally define WOM as "oral, person-to-person communication between a perceived noncommercial communicator and a receiver concerning a brand, a product, or a service offered for sale". This definition assumes that WOM is interpersonal communication, i.e., each WOM is conveyed from a sender to a receiver. Reviewing the early WOM literature, Nyilasy (2005) divided it into four research areas (questions), namely what makes senders talk, why do receivers listen, what happens to the senders after the WOM event, and what is the impact of WOM on receivers. Since Arndt's definition ignores mass communication and other new impersonal channels, especially computer-mediated communications, Hennig-Thurau, Gwinner, Walsh, and Gremler (2004, p. 39) extended the traditional definition of WOM to cover electronic WOM (i.e., e-WOM) as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet". Following Nyilasy's framework, King, Racherla, and Bush (2014) provided a recent survey on e-WOM research and identified six major characteristics of e-WOM.

Much of WOM research has been conducted in the service context, where WOM is more influential due to service's intangible and heterogeneous nature (Murray, 1991). Parasuraman, Berry, and Zeithaml (1991); Parasuraman, Zeithaml, and Berry (1988) suggested that customers' perceptions of service quality of a firm has a positive effect on their willingness to recommend the firm. Research has offered evidence that overall service quality affects customers' particular behaviors, including WOM communication (Choudhury, 2014; Zeithaml et al., 1996), post-purchase and repurchase intentions (Boulding, Kalra, Staelin, & Zeithaml, 1993; Kuo, Wu, & Deng, 2009), and customer satisfaction (Davies, Waite, Jayawardhena, & Farrell, 2011). The models in recent studies are more comprehensive. For example, Ng, David, and Dagger (2011) proposed a structural equation model to examine the effects of relationship benefits (confidence, special treatment, and social benefits) on service quality (functional, technical, and relationship quality), and the subsequent influence on WOM behavior. Sweeney, Soutar, and Mazzarol (2014) investigated various conditional factors that have an impact on positive and negative WOM, and how different forms of WOM affect the receiver's willingness to use a service provider. They found that positive WOM, which could be enhanced by brand equity, has more effect on people's choice. Although these works have enriched our understanding of WOM and other customer behaviors in the service context, their effects on firm-related outcomes and firms' optimal response actions have remained largely unexplored (King et al., 2014).

### 2.3. Agent-based modeling

The term *agent* denotes a computing entity with the following characteristics: autonomy, social ability, reactivity, and proactiveness (Wooldridge & Jennings, 1995). Two major agent communities have enormously contributed to agent-related research in the literature.

The first research vein stems from the discipline of distributed artificial intelligence (DAI), which attempts to design smart agents (e.g., robots) and unite them as a multi-agent system. This system is usually hierarchical, where agents may compete, negotiate, and interact with one another in order to accomplish a certain task that a solo agent cannot reach. Therefore, a leader agent is often created to be responsible for allocating resources and coordinating the other agents in the presence of conflicts. Optimization methods are commonly involved when structuring agent behavior. As a result, many complicated and large-scale issues can be well formulated as multi-agent systems. (Barbati, Bruno, & Genovese, 2012) reviewed the optimization problems solved by agent techniques, including scheduling (Cheng, Ng, & Yuan, 2006; 2008), transportation system control (Chen & Cheng, 2010), production planning (Caridi & Cavalieri, 2004), and facility location (Bruno, Genovese, & Sgalambro, 2010).

The other research vein is built on the complex adaptive system (CAS) theory proposed by Holland (1996), a sub-domain of complex systems research. Unlike multi-agent systems with clear overall objectives, CASs are more decentralized so none of the agents is able to control the whole system. Agents have to adapt to and co-evolve with the dynamic CASs in which they exist, allowing the modeler to observe the evolutionary behaviors of the surviving agents and understand the systematic emergent phenomena. ABM/simulation techniques have been widely used to simulate various CASs, such as biological systems (Biava et al., 2011), ecosystems (Levin, 1998), financial markets (Zhang, Li, Xiong, & Zhang, 2010), economies (Farmer & Foley, 2009), and social systems (Holling, 2001). Combined with game theory, complex networks, geographical information systems, heuristic algorithms, and other elements, agent-based models have been established to investigate evolutionary complexity issues in a bottom-up way (see, e.g., Surana, Kumara, Greaves, & Raghavan, 2005; Heppenstall, Evans, & Birkin, 2006; Krause et al., 2006).

Only a few studies have employed the ABM technique to study service management. For example, Hong, Suh, Kim, and Kim (2009) developed an agent-based model to predict users' preferences using context history (sensed data). Based on their preferences, personalized services can be designed and produced. Roorda, Cavalcante, McCabe, and Kwan (2010) suggested the ABM tool be applied to model logistics services and examine their impacts on the freight system. Agent-based service research in a competitive environment has been scant in the literature, except for Kim and Yoon (2014), which attempted to generate new and competitive service concepts based on the anticipated status of a healthcare system. However, the study did not explicitly model the competition mechanism of the service provider agents.

### 2.4. Summary

In view of the above observations, the authors set out to treat the competitive O2O market as a CAS using the ABM technique for the following reasons:

1. Traditional analytical methods become less practical to gain deterministic insights in the extremely complex and dynamic O2O market, which comprises the following elements: joint pricing-location decisions of competing firms, non-linear interactions between merchants and consumers, imperfect knowledge, and a dynamic information sharing mechanism of heterogeneous clients. Therefore a more viable approach is needed to study the complex issues arising from such a market. For example, surveying 285 journal articles on competitive location problems from 1979 to 2010, Biscaia and Mota (2013) suggested that the future of this field "depends on the researchers' capacity of finding an (even more) interesting and innovative way of modeling spatial competition".
2. Both firms and customers can be modeled as agents, since they carry out tasks independently and have the full features of a typical agent. Comparing with traditional analytical methods, individual-level modeling allows us to focus on the firms and customers. In other words, researchers are able to create, e.g., a large number of customer agents heterogeneous in psychographic variables such as value, attitude, interest, and lifestyle, which are very important in shaping their purchasing behaviors (Zhang & Zhang, 2007). Moreover, they can be made adaptive in competition by introducing a suitable learning mechanism from the discipline of artificial intelligence (AI).
3. Optimal joint decisions on pricing, location, and service quality management can be viewed as adaptive behaviors in competition. According to the CAS theory, it is adaptation that engenders complexity (Holland, 1996). Adaptive agents respond iteratively to feedback by seeking optimal policies and changing their actions in order to survive the "natural selection" process, which is the driving force of evolution in biology. Therefore, given individual objective functions, the optimal service operations can be derived from observing the evolutionary behaviors of surviving firms as emergent phenomena. We then focus on the overall policies of firms in response to competition throughout the evolution of the agent-based model, rather than the specific optimal solutions of individuals in static competition in traditional models.

To sum up, ABM provides a natural and dynamic representation of service businesses with competitive and complex interaction structures to yield powerful insights into evolutionary service management in the highly competitive O2O market.

## 3. Model description

### 3.1. Overall structure

The ACOM explicitly models micro-scale interactions among the agents and macro-scale feedback of market transactions. Fig. 1 shows the overall structure of the ACOM, which consists of one *market*, several competing *firms* that own *stores* and provide services with uncertain quality, and a specified number of *customers* connected by their social relationships, which are illustrated as imaginary lines.

In order to make the ACOM more realistic, the authors borrow and extend many traditional and widely accepted assumptions from location models and consumer behavior research. In particular, underlying the ACOM are the following basic but essential notions in the context of a competitive O2O market.

- Each firm only provides one unique service for all the customers,[1] e.g., Firm 1 provides Service 1 (denoted by $SVC_1$ in Fig. 1) while Firm 2 provides Service 2. These services are substitutable for the customers so there is competition among the firms.
- All the costs (i.e., fix operating cost of all the stores and marginal cost of all the services) are assumed to be identical for each firm. This assumption follows the idea of Grönroos (1994) that over-emphasizing cost reduction in service management is not necessary because it will damage service quality. As a result, all the services have equal expected quality in the ACOM, so all the firms can compete fairly.
- The quality of each service follows an uniform distribution as in Zhang and Zhang (2007) and Izquierdo and Izquierdo (2007). In the ACOM, the means of these distributions are the same by the previous assumption while their boundaries may be different. This is reasonable because it is such variability in service that causes the gap between customer's perception and expectation and attracts much research interest on service quality evaluation and management. Besides, since it is difficult to measure and control service quality precisely, merchants in reality commonly use a quality-control chart to track changes in quality between an upper control limit (UCL) and a lower control limit (LCL) (Fitzsimmons & Fitzsimmons, 2011) with the assumption that all the variations in quality within the two limits are acceptable. Firms may make a strong effort to reduce quality variance by, e.g., standardizing the service workflow so that customers are more likely to have a relatively stable perception of its service, while other firms could empower their employees and encourage them to deal with the diversity in customer contact situations in a proactive way, resulting in greater variability in customer experiences (Grönroos, 1990; Izquierdo & Izquierdo, 2007).
- Due to the uncertainty in service quality, there are no reliable quality indicators for customers before the service encounter takes place (Fitzsimmons & Fitzsimmons, 2011). However, customers are able to update their expected quality of a given service based on their previous purchase experience and/or other customers' recommendations and discouragement via their social relationships (Parasuraman et al., 1985).
- Each customer in the ACOM can be connected to none, one, or several customers called his/her "neighborhood". In reality, they could be the customer's family members, friends, opinion leaders, or someone who exerts a tacit or explicit influence on his/her purchase decisions (Hoyer & MacInnis, 2007). Therefore,

[1] The multiple services case is not considered in this paper because it significantly extends the model boundary and will result in exceedingly high complexity in the ACOM. For example, we need to define the interrelationships among the services (are they substitutable, supplementary, or independent of one another?) and examine the impacts of services' interrelationships on the experimental results. We also need to consider the number of service types that any of the firm/store agents offers, the marginal cost of each service, and the reasons to justify these settings. Moreover, given large numbers of services, it will be difficult to find the optimal behaviors of customers, firms, and stores. The above issues, which exist in the real world, are beyond the scope of this paper to address.

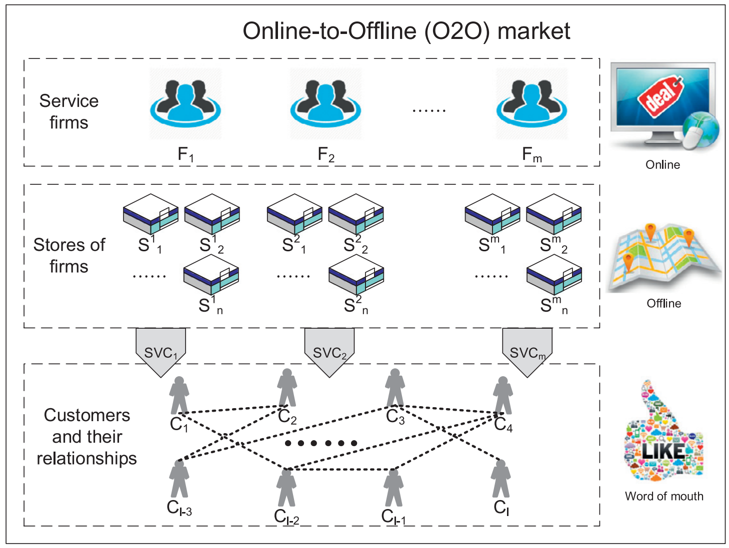



**Fig. 1.** An example of the overall structure of the ACOM, which is assumed to be a CAS consisting of four types of agents: *the market*, *firms* that own *stores*, and *customers*.

the ACOM considers social influence on customer behaviors in an uncertain environment.

- Each service firm owns several stores and all the stores of a given firm charge the same price for the service, as the case with many *Groupon* merchants. Besides, customers are able to access information about the service price and store locations of any firm from its O2O webpage.
- The market agent is modeled as a two-dimensional (2D) plane with size ($X$, $Y$) for an ($x$, $y$) coordinate in the ACOM. Other agents, except firms, are represented as discrete points and placed in the virtual city according to their coordinates. Store agents are moveable while customer agents are not. The Euclidean distances measure the distances between the agents while the customers have to bear the transportation cost. These settings follow most of the facility location models in the literature, e.g., PMAXCAP (Serra & ReVelle, 1999).

In the following we discuss the various components of the model in detail and explain the behavior of each agent in a static time step as a snapshot of the ACOM. Table 1 summarizes the parameters and variables used in the ACOM.

### 3.2. Customers' behaviors

Since OR researchers mainly focus on optimizing firms' decisions, customers' behaviors are often modeled simply even in the location problems where patronizing rules have to be considered. For example, customers patronize the closest vendor in Hotelling's model, while customer patronize the retailer with the lowest total price (transportation cost and mill price) in PMAXCAP. Previous research has largely neglected customers' evolutionary behaviors and often assumes that the consumers exist in a static environment. On the contrary, customers in fact have the power through their fast-changing behaviors to influence the evolution direction of firms' optimal decisions in today's dynamic and competitive business environment (He, Wang, & Cheng, 2013). There is a large body of literature on consumer behavior that aids our understanding of consumer purchase decisions. Borrowing the classical customer decision process from the EKB model proposed by Engel, Kollat, and Blackwell (1973), we model a rational customer agent's purchase behavior in the ACOM, which is divided into four stages in each time step, namely information search, alternative evaluation, purchase decision, and expectation update.

Step 1: Information search. A typical customer (e.g., $C_k$) collects comprehensive service information from the O2O platform, including the service price and locations of nearby stores (e.g., $S^i_j$) of each firm (e.g., $F^i$) at time $t$. Therefore, when patronizing $S^i_j$ that is the closest store owned by $F^i$, customer $C_k$ faces the following full price every time:

$$FP^i_{k,t} = P^i_t + \nu \cdot d_{jk,t}. \tag{1}$$

In Eq. (1), the impact of location on customer's purchase decision is established as a part of the full price of a given service (i.e., $d_{jk,\,t}$) and $\nu$ is the weight for it. Note that the searching cost that may exist in reality is ignored in the ACOM because such information can be conveniently obtained by subscribing for online platforms like *Groupon* or *Yelp*. As mentioned before, the services in the ACOM are heterogeneous and their quality is variable and unobservable, so customers do not know the exact quality ($\phi^i_{k,t}$) of a specific service ($SVC^i$) unless they eventually purchase and experience it. However, customers are still able to make their final decisions based on the expected quality of $SVC^i$ (i.e., $\hat{\phi}^i_{k,t}$), which can be learned from personal and neighbors' experiences, if any.

Step 2: Alternative evaluation. It is assumed that each customer has all the necessary information of each service after online searching. The rational customers will adopt a utility function (also often called the attraction function in many facility location models) taking all the available information into account (Drezner & Eiselt, 2002). In the ACOM, there are $m$ firms varying not only in their stores' locations but also in their service prices. Therefore, in terms of the parameters and variables of the model shown in Table 1, customer $C_k$'s purchase decision problem, in which the customer's goal at time $t$ is to maximize his/her utility, is expressed as follows:

$$U^i_{k,t} = \left(\frac{FP^{max}_{k,t}}{FP^i_{k,t}}\right)^{\alpha_k} \cdot \left(\frac{\hat{\phi}^i_{k,t}}{\hat{\phi}^{min}_{k,t}}\right)^{\beta_k}, \tag{2}$$

where

$$FP^{max}_{k,t} = \max\{FP^i_{k,t}\}^m_{i=1}, \tag{3}$$

$$\hat{\phi}^{min}_{k,t} = \min\{\hat{\phi}^i_{k,t}\}^m_{i=1}. \tag{4}$$

As shown in Eq. (2), two attributes (i.e., full price and expected quality) of the service $SVC^i$ have convex preferences represented

**Table 1**
Variables and parameters used in the ACOM at time $t$.

| Agent type and sample | One firm $F^i$ with one of its stores $S^i_j$ | One customer $C_k$ |
|---|---|---|
| Counts | Number of firms: $m$. Each firm has $n$ stores. | Number of customers: $l$ |
| Decision variables | Location of each store: $(x^i_{j,t}, y^i_{j,t})$<br>Service price: $P^i_t$ | Purchase times for $SVC^i$: $q^i_{k,t}$ |
| Objective | Total profit: $TPR^i_t$ | Utility: $U_{k,t}$ |
| Constraints | $x^i_{j,t} \in [0, X], y^i_{j,t} \in [0, Y]$<br>$P^i_t \geq MC$ | Budget: $B_k \geq q^i_{k,t} \cdot FP^i_t$ |
| Endogenous variables | Purchase times of customers at $S^i_j$: $Q^i_{j,t}$<br>Number of customers who patronize $S^i_j$: $nc^i_{j,t}$<br>Profit of $S^i_j$: $PR^i_{j,t}$ | Distance to closest store $S^i_j$: $d_{jk,t}$<br>Full price when patronizing $S^i_j$: $FP^i_{k,t}$<br>Perceived quality of $SVC^i$: $\phi^i_{k,t} \sim U(LCL^i, UCL^i)$<br>Expected quality of $SVC^i$: $\hat{\phi}^i_{k,t}$ |
| Exogenous variables | Marginal cost of service: $MC$<br>Fixed operating cost of each store: $FC$<br>Boundaries of service quality distribution: $U(LCL^i, UCL^i)$<br>The population size in GA: $ps$<br>Probability of cross over in GA: $pc$<br>Probability of mutation in GA: $pm$ | Unit transport cost divided by distance: $\nu$<br>Sensitivity weight of service price: $\alpha_k$<br>Sensitivity weight of service quality: $\beta_k$<br>Sensitivity weight of personal influence: $\lambda^{ind}_k$<br>Sensitivity weight of social influence: $\lambda^{soc}_k$ |

by a Cobb–Douglas utility function in a multiplicative fashion. Both components in the utility function are greater than or equal to 1 according to Eqs. (3) and (4). The first component refers to the interaction between consumers and service firms as it combines the price and location information determined by firms. While the other component stands for the interaction among heterogeneous customers because the service quality is exogenous and consumers share their service experiences with one another by WOM ($\hat{\phi}^i_k$) in the last stage of their purchase behaviors.

Step 3: Purchase decision. Because of the inseparability feature of services, customer $C_k$ should make the final decision on the number times of acquiring each service in a single period based on complete information on price and incomplete knowledge of service quality. The purchase count at time $t$ is defined as follows:

$$q^i_{k,t} = \begin{cases} \left\lfloor \dfrac{B_k}{P^i_t + \nu \cdot d_{jk,t}} \right\rfloor, & \text{if } U^i_{k,t} = \max\left\{U^i_{k,t}\right\}^m_{i=1}; \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

Eq. (5) denotes that if $SVC^i$ at $S^i_j$ offers $C_k$ the largest utility, customer $C_k$ will allocate all his/her budget to this service deal following the "all or nothing" assumption in PMAXCAP. Note that the sum of all the consumers' purchase times ($q^i_{k,t}$) makes up the total demand ($Q^i_{j,t}$) for store $S^i_j$, which will be further discussed later.

Step 4: Expectation update. Suppose that $C_k$ has experienced $SVC^i$s from $S^i_j$, the real quality of which at time $t$ ($\phi^i_{k,t}$) is known. So the expected quality of $SVC^i$ for the next purchase decision ($\hat{\phi}^i_{k,(t+1)}$) will be updated based on this transaction following the reasoning of Izquierdo and Izquierdo (2007). That is, after each transaction session $t$, $C_k$ updates his/her expected quality of $SVC^i$ if and only if:

- $C_k$ has purchased some $SVC^i$s and he/she somewhat considers his/her own experience (i.e., $0 < \lambda^{ind}_k \leq 1$), or
- someone in $C_k$'s neighborhood (e.g., $C_h$) has purchased some $SVC^i$s and $C_k$ somewhat considers his/her neighbors' experience (i.e., $0 < \lambda^{soc}_k \leq 1$).

More precisely, $C_k$ updates $\hat{\phi}^i_{k,(t+1)}$ according to the following rules:

(a) If both $C_k$ and someone like $C_h$ have purchased $SVC^i$, then

$$\hat{\phi}^i_{k,(t+1)} = \hat{\phi}^i_{k,t} + \lambda^{ind}_k \cdot (\phi^i_{k,t} - \hat{\phi}^i_{k,t}) + \lambda^{soc}_k \cdot (\bar{\phi}^i_{k,t} - \hat{\phi}^i_{k,t}), \quad (6)$$

where $\bar{\phi}^i_{k,t}$ is the average quality of $SVC^i$ received by the customers in $C_k$'s social neighborhood.

(b) If $C_k$ has purchased $SVC^i$ but none in his/her neighborhood has, then

$$\hat{\phi}^i_{k,(t+1)} = \hat{\phi}^i_{k,t} + \lambda^{ind}_k \cdot (\phi^i_{k,t} - \hat{\phi}^i_{k,t}). \quad (7)$$

(c) If $C_k$ has not purchased $SVC^i$ but someone like $C_h$ has, then

$$\hat{\phi}^i_{k,(t+1)} = \hat{\phi}^i_{k,t} + \lambda^{soc}_k \cdot (\bar{\phi}^i_{k,t} - \hat{\phi}^i_{k,t}). \quad (8)$$

Eq. (6) implies that updating customer's service quality expectation is usually affected by two factors, namely personal and neighbors' past experiences (i.e., WOM). For $C_k$, the parameters $\lambda^{ind}_k$ and $\lambda^{soc}_k$ measure his/her sensitivity to the two factors, respectively. Eqs. (7) and (8) are special cases of Eq. (6) when one factor is missing.

By now, customers' behaviors in the ACOM are eventually modeled under the EKB framework by combining individual-level behavioral rules of sharing WOM. It is worth noting that there are four important exogenous parameters that characterize $C_k$, namely $\alpha_k$, $\beta_k$, $\lambda^{ind}_k$, and $\lambda^{soc}_k$. According to the purchase motivation model developed by Zhang and Zhang (2007), they are $C_k$'s personality traits and formally known as price sensitivity, quality sensitivity, susceptibility, and follower tendency. It is personality traits that describe consumers and calibrate the contribution of relevant external stimuli to customers' final decisions. In reality, the values of these parameters vary significantly because people are heterogeneous. For example, an unemployed person may be more price sensitive than a millionaire who may pay more attention to service quality (Zhang & Zhang, 2007), i.e., the millionaire has a greater $\beta$. Besides, Korean consumers may be more susceptible to normative influence than U.S. consumers because of culture differences (Taylor, Miracle, & Wilson, 1997), i.e., Korean consumers have a greater $\lambda^{soc}$. In the ACOM, random values are assigned to these traits in order to generate heterogeneous consumers (see Section 4.1) in the simulation experiments.

In conclusion, the customer agents in the ACOM are heterogeneous and utility-maximizing. They face a trade-off between quality and quantity under a limited budget constraint, and they are able to search for price information, make rational comparisons among available services, and learn from previous personal and neighbors' experience to make purchase decisions.

### 3.3. Firms' behaviors

In response to competition for the limited demand of customers, profit-maximizing firms and their stores dynamically change their pricing and location decisions to adapt to the competitive O2O market. Given these decisions as independent variables, the objective function of $F^i$, which owns $n$ stores, can be written as follows:

$$\max\ TPR^i(P^i, \{(x^i_j, y^i_j)\}^n_{j=1}) = \sum_{j=1}^{n} PR^i_j, \tag{9}$$

subject to

$$P^i \geq MC, \tag{10}$$

$$0 \leq x^i_j \leq X, \tag{11}$$

$$0 \leq y^i_j \leq Y, \tag{12}$$

where

$$PR^i_j = (P^i - MC) \cdot Q^i_j - FC^i_j, \tag{13}$$

$$Q^i_j = \sum_{k=1}^{nc^i_{j,t}} q^i_k. \tag{14}$$

Eq. (9) represents that each competing firm seeks the optimal decisions to maximize its total profit $TPR^i$ that comprises all its owning stores' profits. As described by Eq. (13), each store bears its fixed operating cost $FC^i_j$ and the marginal cost of service $MC$, and attempts to capture more customers for greater demand $Q^i_j$ defined by Eq. (14). The barrier to tackling this problem is the customer demand at each store $q^i_{jk}$, which is a function of all the firm's decisions and clients' interactions as discussed in the section on customers' behaviors. In other words, precise prediction of customer demand requires full knowledge about all the customers' personality traits and rivals' reactions, which is impossible to achieve neither in the ACOM nor in reality. Therefore, it is infeasible to directly find the optimal decisions for firms using traditional OR-based mathematical methods due to complexity, dynamics, and non-linear feedback in customers' behaviors and imperfect knowledge.

To address the above optimization problem, a hybrid approach is proposed following the idea of the price-location heuristic algorithm by Serra and ReVelle (1999). In particular, each store attempts to obtain the best location while the service firm tries to search for the most competitive price. These two procedures are performed simultaneously to avoid sub-optimality (Hanjoul, Hansen, Peeters, & Thisse, 1990; Serra & ReVelle, 1999).

### 3.3.1. Location decisions

Bruno et al. (2010) have demonstrated that the multi-facility competitive location problem on a plane can be solved by ABM, assuming that each agent (facility) iteratively changes its location regulated by two forces, namely a pull force from demand nodes and a repulsive force from other agents. The authors adopt this approach to address the multi-store location issue in the ACOM by excluding the repulsive force for two reasons: if two stores are operated by different firms, such force should not be considered as they could co-exist closely, known as Hotelling's "main street" effect (Hotelling, 1929); if they are owned by the same firm, the demand-driven force will automatically separate them since each customer agent is assumed to choose its nearest store only.

As illustrated by sample problems by Bruno et al. (2010), solving the multi-store location problem in this way amounts to minimizing the total transportation cost for each store's customers in the current time step, similar to the classical $p$-median problem introduced by Hakimi (1965). In essence, the location rule in the ACOM is a greedy algorithm yielding a locally optimal location solution in a step-by-step manner. Therefore, it could approximate a global optimal solution in a reasonable time.

Based on the above discussion, a firm's location decision can be broke down by authorizing its stores to search for the optimal sites for themselves. Suppose that $nc^i_{j,t}$ consumers patronize $S^i_j$ at time $t$, the objective function of $S^i_j$ is expressed as follows:

$$\min\ TC(x^i_{j,t}, y^i_{j,t}) = \sum_{k=1}^{nc^i_{j,t}} (q^i_{k,t} \cdot d_{jk,t}), \tag{15}$$

subject to Constraints 11 and 12. Eq. 15 represents that for store $S^i_j$, the demand $q^i_{k,t}$ reflects the importance of customer $C_k$. In the ACOM, the new destination of store $S^i_j$ at time $t+1$ moves towards the demand-weighted mean of its customers in the previous time step.

### 3.3.2. Pricing decisions

In the ACOM, each competing firm will search for its optimal pricing strategy to maximize its total profit $TPR^i$. Note that there is a constraint (Constraint 10) on pricing adjustment, i.e., $P^i$ of $SVC^i$ must be greater than its marginal cost $MC$. With this constraint, the firms will not engage in a price war regardless of their costs.

A genetic algorithm (GA) is applied to produce approximate optimal solutions to maximize profit through heuristically searching the feasible solution space. Compared with other heuristic techniques to tackle optimization problems, GA mimics the natural selection process and the mechanism of population genetics. This feature makes GA a promising technique to find the optimal decisions of the service firms by evaluating the evolutionary behaviors, given that firms are selected by customers. Moreover, previous works (see, e.g., Heppenstall, Evans, & Birkin, 2007; He et al., 2014) have demonstrated that GA is a popular and effective approach to assist agents in making decisions. In the ACOM, the GA applied to search for the optimal $P^i$ follows the following steps:

Step 1. Generate an initial population of possible solutions randomly by assigning random values to $P^i$ as individuals.
Step 2. Compute $TPR^i_t$ as the fitness of each individual in that population.
Step 3. Select two best-fit (maximal $TPR^i_t$) individuals ($\{P^{i,*}_t\}$) for reproduction at time $t$.
Step 4. Encode $\{P^{i,*}_t\}$ in binary as strings of 0s and 1s.
Step 5. Breed a new individual ($\{P^{i,\prime}_{t+1}\}$) through the cross-over and mutation operations to give birth to offspring.
Step 6. Evaluate the individual fitness ($TPR^i_{t+1}$) of the new individual at time $t+1$.
Step 7. Replace the least-fit population with the new individual.
Step 8. Go to Step 3 until termination.

With GA, the service firms are able to "memorize" their good pricing strategies that generated high fitness in the past time steps. At the same time, their stores are also optimizing the location decisions. Therefore, the intelligent agents are capable of evolving towards better strategies to optimize their objectives by interacting with the complex environment.

## 3.4. The market's behaviors

The market agent in the ACOM can be viewed as a container that keeps the firms, stores, and customers in it. It performs three important tasks to make the ACOM complete. First, the market needs to update the values of all the variables, such as price, position, and other endogenous parameters defined in the ACOM. Second, if the ACOM meets the stop criteria, the market will terminate the simulation and output detailed statistical data for further analysis. Third, the market agent is in charge of drawing the other agents, especially stores, in order to reflect the evolution of the ACOM in terms of location.

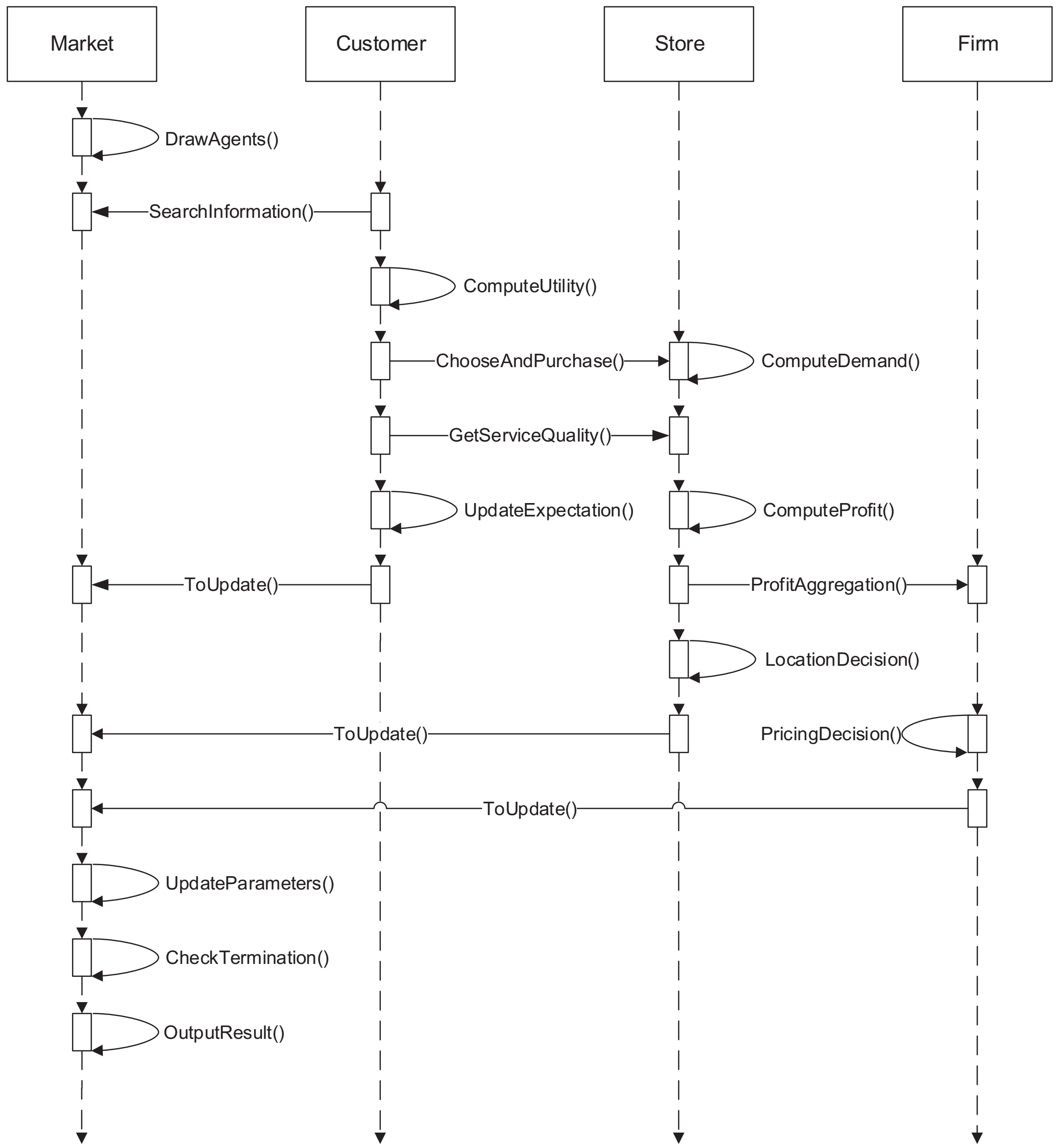



**Fig. 2.** UML time sequence diagram of the ACOM.

*3.5. Summary*

This section explicitly defines the agents' attributes and behaviors interacting with their peers and other agents. Before starting the simulation experiments, the agents' behaviors should be scheduled in a time step for implementation in the computer simulation programs. Fig. 2 summarizes the sequence of events in the ACOM in the form of a unified modeling language (UML) behavior diagram. We have elaborated on all the components in this section.

In the next section we discuss the simulation experiments performed to examine the interactions among *the market*, *firms*, *stores*, and *customers*, and derive insights from the simulation results.

**Table 2**
Values of parameters that remained unchanged in the simulation experiments.

| Parameter | Value |
|---|---|
| $m$ | 2. The two firms are denoted by $F^1$ and $F^2$. |
| $l$ | 55. |
| $pc$ | 0.1. |
| $pm$ | 0.05. |
| $ps$ | 10. |
| $(X, Y)$ | $X = Y = 65$. |
| $v$ | 1. |
| $n$ | 2. They are $S_1^1$, $S_2^1$, $S_1^2$ and $S_2^2$. |
| $MC$ | 10. |
| $FC$ | 0. |
| $\alpha_k, \beta_k$ | $\alpha \sim U(0, 1)$. $\beta = 1 - \alpha$. |

## 4. Simulation

*4.1. Experimental design*

Eight experiments are conducted using the ACOM under two different scenarios, namely Scenario A and Scenario B. Table 2 presents the parameters that remained unchanged in all the experiments. Most parameters' values, such as the number of agents and customers' budgets, locations and their social links, come from the "55-node network" in the original PMAXCAP (see Fig. 1 and Table 3 by Serra and ReVelle (1999) for the full data) as a benchmark for validating the ACOM. Besides, we assigned random values to $\alpha$ and $\beta$, but kept them unchanged in all the experiments.

**Table 3**
Values of parameters that changed in the simulation experiments.

| Parameters | Scenario A | | | Scenario B | | | | |
|---|---|---|---|---|---|---|---|---|
| | Exp. A1 | Exp. A2 | Exp. A3 | Exp. B1 | Exp. B2 | Exp. B3 | Exp. B4 | Exp. B5 |
| $(LCL^1, UCL^1)$ | (20,20) | (20,20) | (20,20) | (20,20) | (20,20) | (20,20) | (20,20) | (20,20) |
| $(LCL^2, UCL^2)$ | (20,20) | (15,25) | (10,30) | (10,30) | (10,30) | (10,30) | (10,30) | (10,30) |
| $\lambda^{ind}$ | 1 | 1 | 1 | 0.8 | 0.6 | 0.4 | 0.2 | 0 |
| $\lambda^{soc}$ | 0 | 0 | 0 | 0.2 | 0.4 | 0.6 | 0.8 | 1 |
| $(x^i_{j,0}, y^i_{j,0})$ | Random initial position for store agents. | | | | | | | |

There are four important parameters varied among the eight experiments as listed in Table 3: $LCL^i$, $UCL^i$, $\lambda^{ind}$, and $\lambda^{soc}$. The former two control the range of variations in service quality ($\phi^1 \sim U(LCL^1, UCL^1)$, $\phi^2 \sim U(LCL^2, UCL^2)$). Changing their values helps us to study the impact of service quality uncertainty on firms' pricing and location decisions.

Scenario A is designed to validate the ACOM and understand the relationship between joint pricing-location decisions and service quality variability. Validation is a crucial step in modeling ABMs (Bonabeau, 2002). Therefore, consumers' information sharing is excluded (i.e., $\lambda^{soc} = 0$) and thus the ACOM is comparable to location models like PMAXCAP. We are also interested in how increasing service quality variability affects firms' optimal decisions, which could generate managerial insights for some O2O markets where WOM is relatively less significant.

Under Scenario B, we attempt to examine changes in the evolutionary behaviors of firms facing heterogeneous customers that are able to learn from their neighbors' experiences when they make purchase decisions. As $\lambda^{soc}$ increases, customers will generally pay more attention to WOM in the ACOM. We can observe the evolutionary pricing and location decisions of two service firms under different scenarios and thus answer the question: What are the impacts of more socialized customer behavior on these decisions?

### 4.2. Implementation and performance measures

Simulation experiments were conducted using the ACOM on the Swarm v2.2 platform with Java programming codes. Each experiment was performed with the ACOM under the two scenarios 100 times to ensure robust outputs against the randomness in GA, stores' initial positions etc. We carried out the steps presented in Fig. 2 over 500 time steps for each experiment to achieve dynamic equilibrium through evolution. Specifically, we focused on the following indicators in order to generate insights:

1. Prices offered by the two firms: $P^1$, $P^2$.
2. Average weighted distance between customers to stores owned by the firms: $\overline{d}^1$, $\overline{d}^2$ (e.g., $\overline{d}^1 = \frac{1}{nc^1}\sum_{k=1}^{nc^1}(q^1_k \cdot d^1_k)$).
3. Purchase times of firms' services: $Q^1$, $Q^2$.
4. Profits of the firms: $TPR^1$, $TPR^2$.
5. Numbers of customers captured by the firms: $nc^1$, $nc^2$.
6. Average expected service quality of customers: $E(\hat{\phi}^1)$, $E(\hat{\phi}^2)$ (e.g., $E(\hat{\phi}^1) = \frac{1}{nc^1}\sum_{k=1}^{nc^1}\hat{\phi}^1_k$).

The metrics $P^1$ and $P^2$ are the pricing decisions of the two firms. For the ACOM, it is difficult to find a perfect indicator to reflect firms' overall location decisions since they have more than one store being dynamically relocated on the plane. As a result, two indicators $\overline{d}^1$ and $\overline{d}^2$ are introduced to approximately represent the degree that firms are close to their customers. The authors also take screenshots to demonstrate their optimal locations at the end of each experiment. Besides, $Q$, $TPR$, and $nc$ measure firms' performance in the face of competition and $E(\hat{\phi})$ provides information on the overall service quality expectation of consumers.

**Table 4**
The means and standard deviations of the indicators under Scenario A.

| Index | Exp. A1 $UCL^2 - LCL^1 = 0$ | Exp. A2 $UCL^2 - LCL^1 = 10$ | Exp. A3 $UCL^2 - LCL^1 = 20$ |
|---|---|---|---|
| $P^1$ | 59.6(16.4) | 60.4(15.4) | 63.5(15.4) |
| $P^2$ | 59.1(16.3) | 55.0(16.8) | 53.5(17.0) |
| $\overline{d}^1$ | 6.5(3.7) | 9.7(0.5) | 9.8(0.4) |
| $\overline{d}^2$ | 6.4(3.7) | 6.9(3.3) | 7.5(3.2) |
| $Q^1$ | 32.5(28.5) | 36.1(19.6) | 39.3(16.0) |
| $Q^2$ | 27.1(25.6) | 26.4(22.0) | 21.0(16.9) |
| $\hat{\phi}^1$ | 16.6(7.6) | 20.0(0.0) | 20.0(0.0) |
| $\hat{\phi}^2$ | 17.0(7.2) | 17.8(6.3) | 18.6(5.8) |
| $nc^1$ | 29.2(22.1) | 35.0(14.2) | 39.4(10.1) |
| $nc^2$ | 25.8(22.1) | 20.0(14.2) | 15.6(10.1) |
| $TPR^1$ | 1337.0(1016.5) | 1613.4(668.3) | 1854.5(458.5) |
| $TPR^2$ | 1186.4(1019.3) | 861.4(614.0) | 651.6(423.4) |

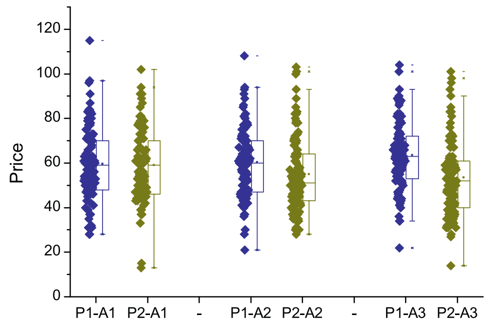
## 5. Results and discussion

### 5.1. Scenario A

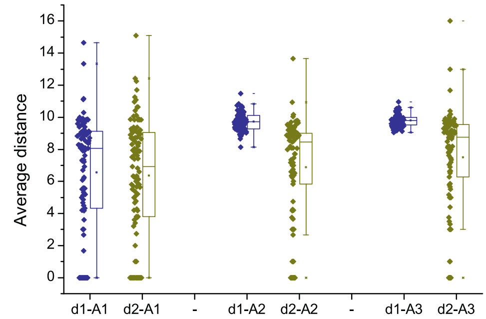
Under Scenario A, customers' expected quality will be updated only if they eventually purchase the service. The authors illustrate all the data output from hundreds of simulations and draw a box plot to show their distributions in Fig. 3. Table 4 presents the means and standard deviations of the above indices in Exp. A1–A3 under this scenario. Besides, we take snapshots for all the experiments in the final time step in Fig. 4.

In the first experiment Exp. A1, the ACOM reduces to a PMAXCAP-like model, given the parameter settings. The absence of quality variability makes the firms and services homogeneous. Moreover, customers will always patronize the store with the lowest full price regardless of its ownership. So it is not surprising that most of firms' indicators presented in Table 4 are almost the same and they share the similar distributions as shown in Fig. 3. For example, firms' prices ($P^1$, $P^2$) are very close to each other. However, the performance of the two firms varies sharply as seen from the huge variances in service time, profit, and number of captured customers.[2] The reason is that each store tends to choose the same location as that of its nearest competitor, which mirrors Hotelling's "main street" effect (see Figs. 3(b) and 4(a)). This "similar location strategy" highlights the importance of the pricing decision. Therefore, firms frequently adjust their prices to capture their customers in the short term, which leads to a big variance in price as illustrated in Fig. 3(a). In other words, we may draw the same

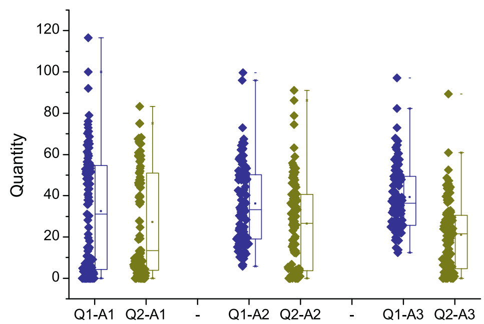
[2] The reader may find that both $\hat{\phi}^1$ and $\hat{\phi}^2$ in Table 4 are not equal to 20 in Exp. A1, which seems incorrect because there is no service quality variability in this experiment. In the ACOM, if and only if one firm temporarily captures all the customers in the market, the market agent will give us the zero expected quality for the other firm, which could help us to examine how many times this situation happens. According to the update rules, the customers' expectations about the defeated firm will actually remain unchanged in the simulation. Therefore, this output rule embedded in the market agent will not affect customers' later choices and the final results of all the experiments either.



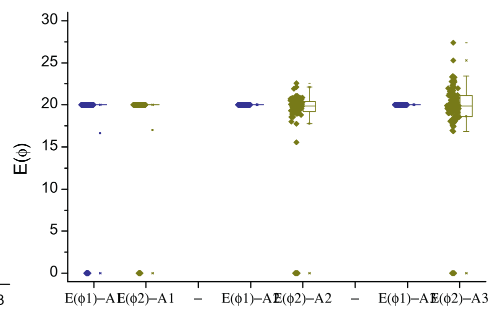

(a) Price



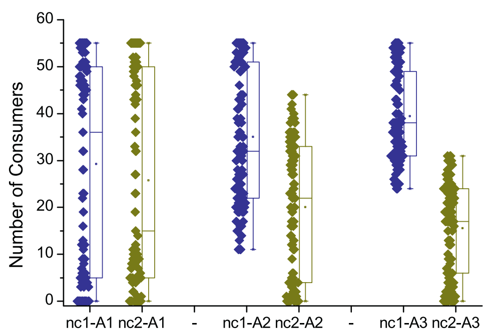

(b) Average Weighted Distance



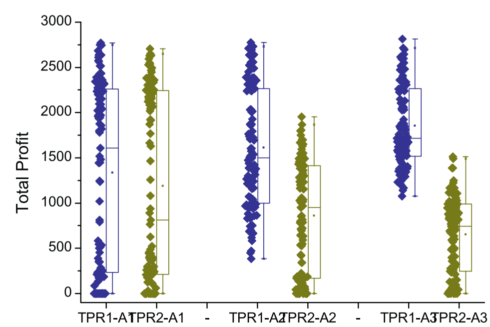

(c) Purchase Times of Services




(d) Expected Service Quality

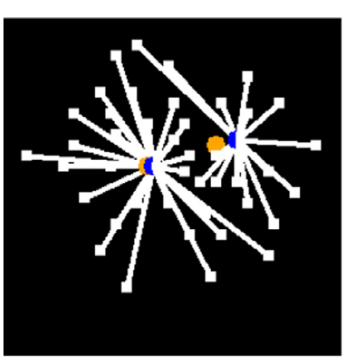



(e) Number of Captured Consumers

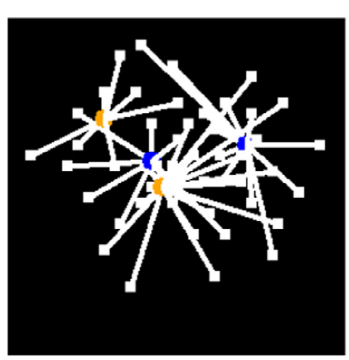



(f) Total Profit

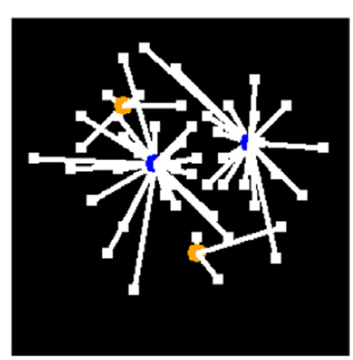
**Fig. 3.** Box plots with data depicting the distribution of results under Scenario A. Box plots are built based on their quartiles ($Q_1$, median, and $Q_3$.), and the ends of the whiskers represent the lowest/highest datum still within 1.5 IQR (interquartile range) of the lower/upper quartile. The square in the box is the mean of the data.



(a) Exp. A1

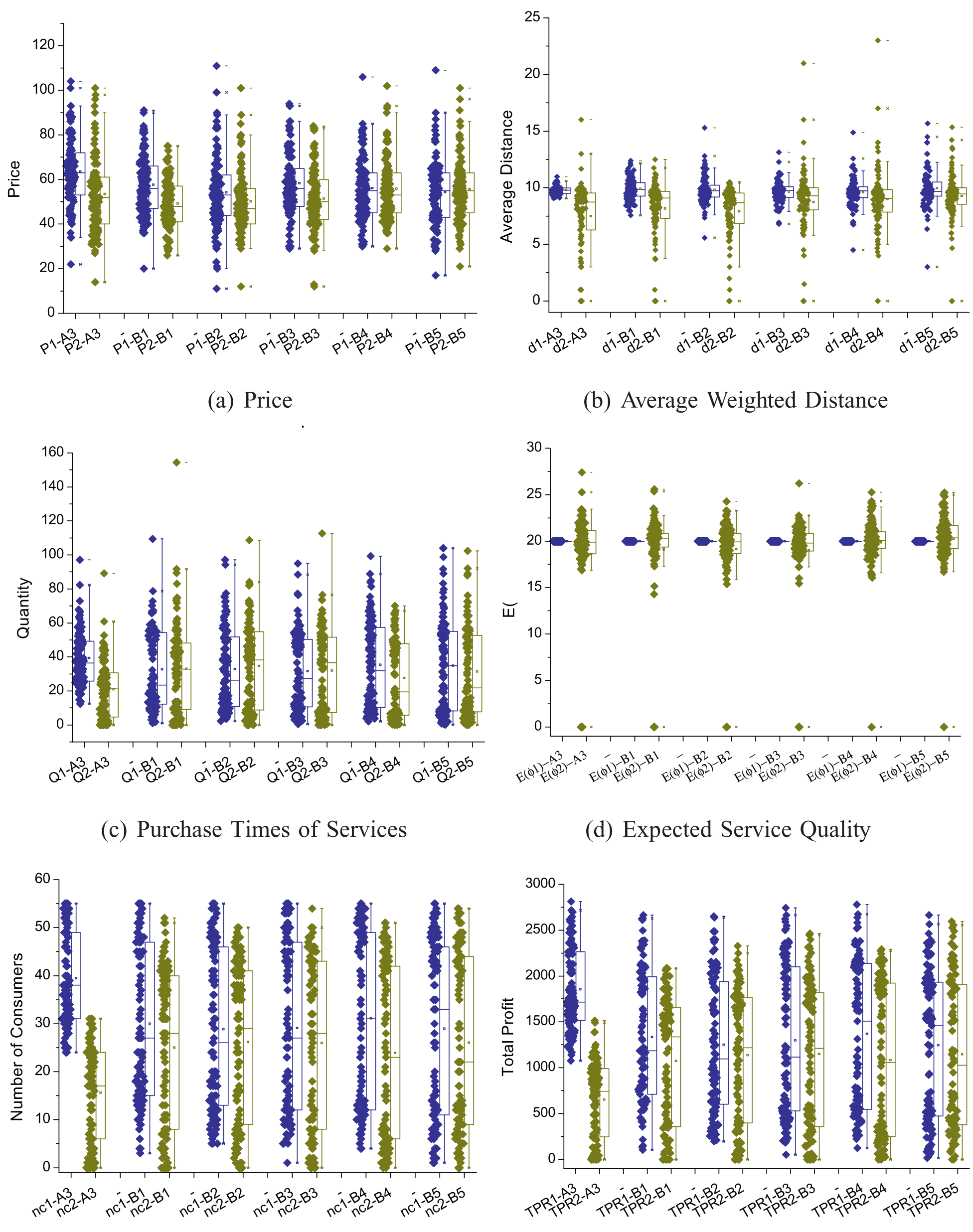


(b) Exp. A2



(c) Exp. A3

**Fig. 4.** The screenshot of the ACOM in the final time step in the three experiments under Scenario A. White squares represent *customers*, blue and yellow circles are *stores* owned by $F^1$ and $F^2$, respectively. Links among agents represent their current supply-demand relationships. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)




(a) Price (b) Average Weighted Distance

(c) Purchase Times of Services (d) Expected Service Quality

(e) Number of Captured Consumers (f) Total Profit

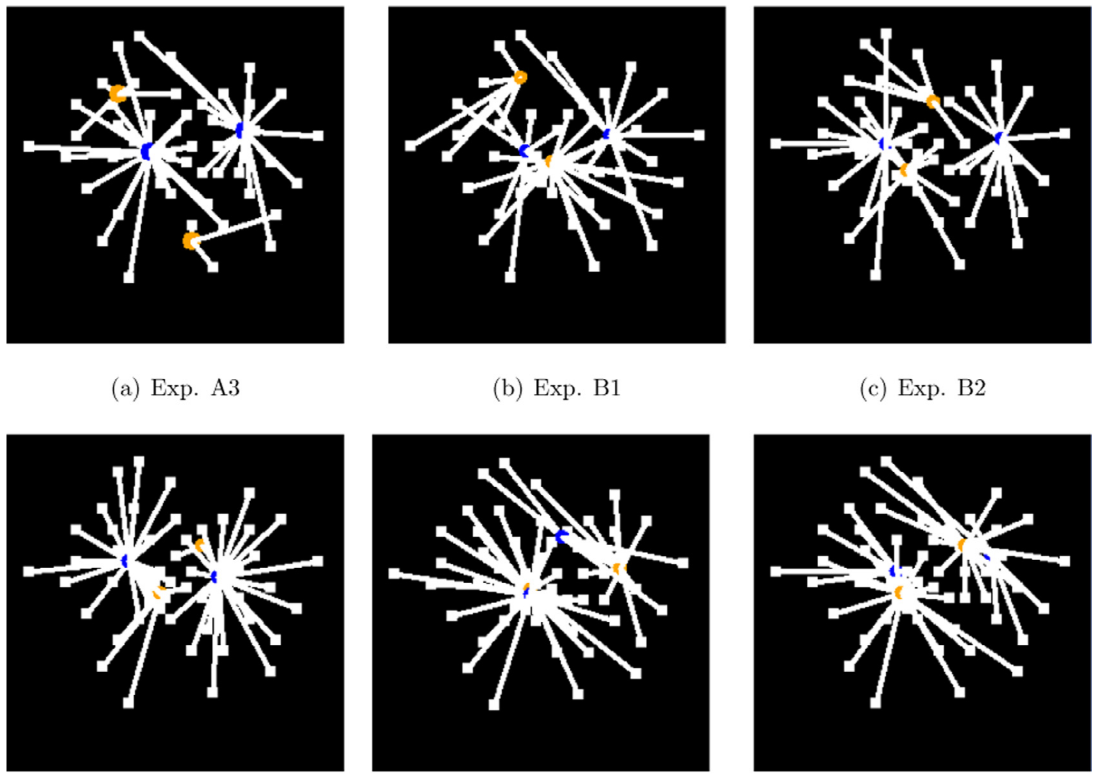
**Fig. 5.** Box plots with data depicting the distribution of results under Scenario B, together with that in Exp. A3. Box plots are built based on their quartiles ($Q_1$, median, and $Q_3$.), and the ends of the whiskers represent the lowest/highest datum still within 1.5 IQR (interquartile range) of the lower/upper quartile. The square in the box is the mean of the data.

conclusion by Hotelling (1929) that no static equilibrium price solution can be found under the homogeneous scenario in the ACOM. Consequently, customers switch from $F^1$ to $F^2$ in the price war. Fig. 3(e) also demonstrates that both firms usually attract either almost all the customers or very few clients. For firms, this causes great uncertainty in demand and extreme fluctuations in their profits, as shown in Fig. 3(f).

As we widen the scope of the distribution that $\phi^2$ follows, the quality of $SVC^2$ becomes more uncertain. Comparing with the results of Exp. A1, $F^1$ has much better performance in all the indicators, especially its profit even though it raises the price. While $F^2$ has to pay for service quality uncertainty, it attempts to attract consumers by reducing its price. This seems to work in Exp A2, where $F^2$ still has 36% of the customers. However, the market share drops to 28% in Exp. A3 because customers refuse to purchase service $SVC^2$ of more variable quality in comparison with $SVC^1$.

Next, we turn our attention to store locations. Note that the demand in the ACOM is non-uniformly distributed, and the point (33.72, 26.78) on the plane is the $p$-median when $p = 1$ according to the locations and budgets of customers. Therefore, it is more likely for firms to capture more clients if their stores are close to the center of the zone.[3] As shown in Fig. 4(b) and (c), the two blue stores owned by $F^1$ occupy the central area where many consumers locate, and the yellow stores are cornered in the market and they defend against the blue ones by being close to the minority customers. It is worth noting that this evolution in location

[3] Serra and ReVelle (1999) demonstrated that when there are fewer stores, firms tend to concentrate in the center of the network in the original PMAXCAP.



(a) Exp. A3 (b) Exp. B1 (c) Exp. B2

(d) Exp. B3 (e) Exp. B4 (f) Exp. B5

**Fig. 6.** The screenshot of the ACOM in the final time step in the five experiments under Scenario A, together with that in Exp. A3. White squares represent *customers*, and blue and yellow circles are *stores* owned by $F^1$ and $F^2$, respectively. Links among agents represent their current supply-demand relationships. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

reflects another location principle: locate away from rivals. The location decision under this scenario, which moves from Hotelling's "main street" to the opposite situation, is solely caused by the increased uncertainty of service quality. Therefore, we agree with Christou and Vettas (2005) that "quality uncertainty affects the location choices of firms".

Moreover, for $F^2$ in the ACOM, if a customer experiences a series of "unsatisfying-enough" services from $F^2$, he/she has a high probability to stop purchasing $SVC^2$ because of individual learning. Given the customers' expectations updating rule and larger variance in service quality, $F^2$ may be less competitive in the ACOM over time.

In conclusion, the experimental results under Scenario A have validated the ACOM, which means that the ACOM is a suitable O2O model for location and pricing research. It is found that service firms which have less variable service quality are able to raise prices without compromising profit and beat the rivals by locating at ideal positions. Therefore, if consumers' information sharing can be ignored, a service merchant should standardize its service management in order to offer a stable expectation to customers, thus reducing customer dissatisfaction. However, if all the competing service firms are providing homogeneous services, they are likely to resort to a price war to compete for clients.

### *5.2. Scenario B*

The five experiments under Scenario B can be viewed as extensions of Exp. A3 because they have the same service quality distribution. The only difference among them is that customers' decisions will be increasingly influenced by external information as $\lambda^{soc}$ increases. In the ACOM, customers obtain and share service quality information with one another. For $F^2$, the presence of variable service quality may engender positive and negative WOM. We are interested in examining what influence would shared WOM bring to the final optimal decisions of customers and service merchants. The relative results of these experiments, together with those of Exp. A3, are shown in Table 5, Figs. 5 and 6.

First, we focus on the remarkable differences between Exp. A3 and Exp. B5, which are the two polarized cases under the same service quality condition. Table 5 indicates that the results for $F^2$ in Exp. B5 are more comparable to the results of Exp. A3. All the indicators of $F^2$ are similar to $F^1$ due to the social learning policy, which narrows the variability in customers' expectations over time because clients can access new service quality information even they did not experience it. Evidence can be found in the increasing mean and decreasing standard deviation of $\hat{\phi}^2$ it in Table 5 from Exp. A3 to Exp. B5. Therefore, shared experience from the neighborhood, social network, and the Internet, could reduce uncertainty in expected service quality and influence customers' purchase decisions (Senecal, Kalczynski, & Nantel, 2005).

Second, as shown in Table 5, the pricing and location indicators of the two firms are coming closer as customers are more subject to social influence. It is also found that the yellow stores in Fig. 6 capture increasing customers and they return to compete against the blue stores for the center position of the plane, which means that $SVC^2$ with the same service quality distribution is more acceptable by customers far away. $F^1$'s absolute advantage in location under Scenario A is challenged here as it has to face a greater variance in the location decisions, as shown in Table 5 and Fig. 5(b).

Moreover, by observing the distribution of the key performance indicators (see Fig. 5(c), (e), and (f)), we find that in the context

**Table 5**
The means and standard deviations of the indicators under Scenario B.

| Index | Exp. A3 $\lambda^{ind}=1, \lambda^{soc}=0$ | Exp. B1 $\lambda^{ind}=0.8, \lambda^{soc}=0.2$ | Exp. B2 $\lambda^{ind}=0.6, \lambda^{soc}=0.4$ | Exp. B3 $\lambda^{ind}=0.4, \lambda^{soc}=0.6$ | Exp. B4 $\lambda^{ind}=0.2, \lambda^{soc}=0.8$ | Exp. B5 $\lambda^{ind}=0, \lambda^{soc}=1$ |
|---|---|---|---|---|---|---|
| $P^1$ | 63.5(15.4) | 57.6(13.4) | 54.2(17.1) | 58.3(14.0) | 56.1(14.2) | 54.3(15.1) |
| $P^2$ | 53.5(17.0) | 49.2(11.4) | 50.2(13.8) | 51.5(14.3) | 55.8(14.1) | 55.7(14.8) |
| $\bar{d}^1$ | 9.8(0.4) | 9.9(0.9) | 9.8(1.2) | 9.7(1.0) | 9.6(1.3) | 10.0(1.7) |
| $\bar{d}^2$ | 7.5(3.2) | 8.2(2.7) | 7.9(2.5) | 8.7(3.0) | 9.0(2.8) | 9.3(2.1) |
| $Q^1$ | 39.3(16.0) | 32.6(23.1) | 32.8(23.8) | 31.5(22.6) | 35.3(25.5) | 34.9(27.6) |
| $Q^2$ | 21.0(16.9) | 33.0(26.5) | 34.7(25.3) | 31.8(24.5) | 27.6(22.9) | 31.3(25.9) |
| $\hat{\phi}^1$ | 20.0(0.0) | 20.0(0.0) | 20.0(0.0) | 20.0(0.0) | 20.0(0.0) | 20.0(0.0) |
| $\hat{\phi}^2$ | 18.6(5.8) | 19.1(5.1) | 19.1(4.2) | 19.0(4.6) | 19.8(3.3) | 20.2(3.4) |
| $nc^1$ | 39.4(10.1) | 30.0(16.2) | 28.9(16.6) | 29.1(17.6) | 31.1(18.1) | 28.9(18.3) |
| $nc^2$ | 15.6(10.1) | 25.0(16.2) | 26.2(16.6) | 25.9(17.6) | 23.9(18.1) | 26.1(18.3) |
| $TPR^1$ | 1854.5(458.5) | 1334.0(704.8) | 1249.4(733.5) | 1295.6(806.3) | 1369.4(802.9) | 1243.6(794.0) |
| $TPR^2$ | 651.6(423.4) | 1073.4(685.1) | 1134.5(703.2) | 1148.7(782.9) | 1083.6(820.9) | 1146.4(811.2) |

of social learning, firms do not always benefit from the effect of increasing $\lambda^{soc}$. In fact, Table 5 also indicates that both firms suffer larger variances in their service times, profits, and numbers of captured consumers. Surprisingly, it seems that Exp. B5 replays Exp. A1, except $E(\hat{\phi}^2)$, under completely different conditions. A reason is provided to account for this phenomenon in the ACOM: it is caused by customers' *herd behavior*, defined as "everyone is doing what everyone else is doing" by Banerjee (1992). As $\lambda^{soc}$ increases, a customer tends to disregard his/her own purchase experience and value the WOM he/she receives. Therefore, he/she and his/her neighborhood may hold a similar attitude towards the service and may make the same purchase decisions. For firms, unexpected group-buying makes their demand unpredictable due to the fast-changing online behaviors of customers who become more attuned to social learning nowadays.

In sum, more socialized customers are valuable to the firms whose service are unstandardised because these clients will receive more WOM from their neighborhood and thus have less variability in the expected service quality. Comparing with the results under Scenario A, we find that it is customers' social learning that facilitates the diversity of services in O2O markets, since these services have good potential to compete against standardized service without having to be homogeneous. As a result, these service firms in competition have more choices in terms of pricing and location decisions. However, the side effect is that, if customers have increasing follower tendency online, their herd behaviors would lead to unpredictable offline demand variations, which consequently poses performance risk to the service firms.

## 6. Conclusions

This paper proposes an agent-based competitive O2O model (ACOM) to investigate the evolutionary location and pricing behaviors of service merchants. The ACOM consists of four types of agents in a two-dimensional plane: (1) Profit-maximizing firm agents provide services with variable quality and pursue suitable pricing strategies. (2) Store agents owned by firms search for optimal location decisions to minimize the total transportation cost, so attracting more clients. (3) Heterogeneous customer agents are uncertain about service quality. Therefore, they learn from personal and neighbors' past experiences (i.e., WOM) to update their expectations, and make purchase decisions under a limited budget constraint. (4) The market agent is a container that keeps the firms, stores, and customers in it. We derive the agents' optimal behaviors in response to competition and evolution using a hybrid approach.

The findings from the simulation outputs of eight experiments under two scenarios can be concluded as follows: (1) If consumers' information sharing can be ignored, a service merchant should standardize its service management in order to offer a stable expectation to customers, so reducing customer dissatisfaction. However, if all the competing service firms are providing homogeneous services, they are likely to resort to a price war to compete for clients. (2) More socialized customers are valuable to the firms whose services are unstandardised because these clients will receive more information from their friends and thus have less variability in expected quality. Therefore, these service firms in competition have more choices in terms of pricing and location strategies. (3) Customers' social learning facilitates the diversity of services in O2O markets; meanwhile, if customers have increasing follower tendency online, their herd behaviors would lead to unpredictable demand variations, which consequently pose performance risk to the service firms.

The ACOM adopts the CAS perspective to model the optimal responses of agents in competition in a bottom-up way, and investigates the evolutionary and competitive location and pricing strategies of firms. The presented approach provides a promising framework and a viable methodology to study complex issues of service management in competitive O2O markets from an academic standpoint. The observed findings provide valuable practical insights for practitioners based on realistic modeling of the behaviors of agents, especially customer agents, in today's fast-changing, increasingly competitive, and complex business O2O environment.

Several directions are suggested for future research. First, it is worth modeling service quality management and other components, such as service capacity constraint, as extensions of the ACOM. Firms' behaviors in the ACOM are relatively simple, so their complex business procedures could be modeled in a reasonable way. Second, one of the research goals of this study to determine the boundary of the ABM. Therefore, some assumptions can be relaxed in an extended version of the ACOM, depending on the research scope of the future work. For example, understanding the structure of the O2O market may require an entrance and exit mechanism so that the service firms can enter and exit the O2O market. If a future study aims to study the multi-service O2O market, the multiple services case should be considered. When designing the ABM, modelers must strike a balance between a limited research scope and unlimited approximation of reality. Finally, it would make agents' behaviors much more realistic if individual-level behavioral data can be collected and used in future research.

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