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Agent-based simulation of consumer purchase decision-making and the decoy effect ☆

Tao Zhang *, David Zhang

Exeter Manufacturing Enterprise Centre (XMEC), School of Engineering, Computer Science and Mathematics, University of Exeter, Room 204, Harrison Building, North Park Road, Exeter, Devon, EX4 4QF, UK

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Abstract

Consumer behavior research involves various areas: psychology, marketing, sociology, economics and engineering. This paper presents an agent-based model (ABM) of consumer purchase decision-making. The core of this model is a motivation function that combines consumers' psychological personality traits with two important kinds of interactions in a competitive market. The model reveals the inner psychological mechanism on the basis of which consumers make their choices when facing competing brands on the market. By creating a large number of heterogeneous consumer agents in an artificial market, this study uses multi-agent simulation (MAS) to exhibit the emergent decoy effect phenomenon, which is a market dynamic phenomenon originating from the individual behavior of heterogeneous consumers and their interactions in the real-world complex market. The combined use of the ABM and the MAS method in studying consumer behavior and markets gives one the potential to cope with the dynamic changes and complexities in the real-world business environment.

Keywords: Agent; Motivation function; Price sensitivity; Quality sensitivity

1. Introduction

The process in which consumers make their purchase decisions has long been of great interest to researchers and practitioners (Burnett and Lundford, 1994). The purchase decision-making process and the interactions among consumers based on this process generate market dynamics, such as the decoy effect and lock-in, which are hard to explain. Research into consumer purchase decision-making and consumers' interactions increases the understanding of such market dynamics. Traditional studies on consumer decision patterns, such as data mining, focus on using static equilibrium-based mathematical and statistical techniques to model consumers' socio-demographic and behavioral data. However, three types of data exist regarding consumer purchase decisions: 1) demographic data, 2) behavioral data, and 3) psychographic data (Rud, 2001). Psychographic data, characterized by attitudes, opinions, lifestyle characteristics, or personal values, are of great importance in consumer purchase decision-making. A challenge to researchers and practitioners is how to use psychographic data to model consumer purchase decision-making as well as dynamically emergent phenomena in markets. This issue involves research in the fields of psychology, economics, sociology and marketing, which is in line with the research of the agent-based computational simulation of complex social systems. Therefore, the newly developed agent concept in artificial intelligence has triggered great expectations to cope with this topic. An agent is a highly abstract concept, and researchers still do not agree about the issues what an agent actually is and what exactly constitutes an agent (Poggi, 1999). The general

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* Corresponding author. Tel.: +44 1392 263613; fax: +44 1392 217965.
E-mail address: TZ207@ex.ac.uk (T. Zhang).

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opinion regarding agents in artificial intelligence is that any entity with some of the following attributes can be considered as an intelligent agent: 1) autonomous behavior, 2) individual world-view, 3) communicative and cooperative capacity, 4) intelligent behavior; and 5) spatial mobility (d'Inverno and Luck, 2004). Based on these characteristics, agents have been widely applied in engineering, computer science, economics, and sociology. Agent-based simulation (ABS) is a bottom-up technique that has offered a robust tool to cope with the complexities in a complex system environment (Grimm et al., 2005). Researchers have used agents in the aforementioned areas to simulate machines, software entities, economic entities, animals, human beings, and human society. In the recent 5 years, the application of agents in marketing research has significantly gained momentum (for example, the CUBES model (Ben Said et al., 2001), the SimStore Model (Casti, 1999), and J-Pop Simulation (Makoto, 2000), and the success of these models has shown that they are effective tools in marketing research. Currently researchers are interested in using agents and multi-agent systems to simulate consumer behavior and marketing dynamics. The purpose of this simulation is to optimize supply chains, evaluate the influence of governmental economic policies on business, and to improve companies' marketing performance in a competitive market by achieving an in-depth understanding of the psychology of consumers and the sociology of consumer groups or networks.

The first step is to develop an agent-based consumer purchase decision-making model based on the classic psychological reasoned action theory (Ajzen and Fishbein, 2005), the conscious intention and motivation concept (McClelland, 1987) and consumer–sociological interactions. The core idea of the model is that each brand of a product can trigger a purchase motivation that drives an agent's purchase decision. When facing multiple purchase choices, the agent will calculate all purchase motivations, compare them, and choose the one that brings the most advantage**.** This paper introduces an algorithm derived from this agent-based consumer purchase decision-making model, to control an agent's buying behavior. The authors present this algorithm in the form of a motivation function. This study has created a virtual market by using a large number of artificial consumer agents to simulate the emergent marketing phenomenon, called the decoy effect. The algorithm controls these agents' buying behaviors. The multi-agent simulation of the decoy effect has validated the effectiveness of the agent-based purchase decision-making model and provided the potential to explore and predict dynamic market variations, e.g. fluctuations in market shares, the influence of economic government policies, technological innovations, and a market's responses to expected or unexpected events. The contents of the sections of this paper are the following:

Section 2 illustrates the consumer purchase decision model currently used in marketing science. This traditional model is a contrast to the newly developed agent-based purchase decision-making model, which highlights the originality of this paper. Traditional marketing models dealing with consumer purchase decision-making focus more on a management point of view. These models identify the many factors that affect consumer purchase decisions and behaviors. However, none of them have revealed the inner psychological process of the consumer purchase decision. By introducing the motivation concept, a psychological term that measures the degree of a consumer's intention to buy a product, the resulting agent-based model can fill this gap.

Section 3 explains the development of the agent-based model in detail. First, the section introduces classical behavior psychology theories, such as reasoned action, planned behavior (Ajzen and Fishbein, 2005), and conscious intention and motivation (McClelland, 1987), which are the fundamental theories of the agent-based purchase decision-making model. Next, the section describes the development of the agent-based model, which is based on consumer psychology and two kinds of sociological interactions in the real market. After that, Section 3 introduces an algorithm to control agents' buying behaviors, taken from the agent-based purchase decision-making model. The algorithm has the form of a motivation function, and the authors make detailed suggestions concerning its form.

Section 4 demonstrates the decoy effect, an emergent marketing phenomenon, by conducting a multi-agent simulation. After introducing the details of the decoy effect, including the concept and recent studies, Section 4 will focus on the simulation experiments, in particular the parameters and variables used, the results, and the analysis of these results. Finally, Sections 5 and 6 point out the originality and significance of the paper, its limitations, and offer suggestions for further research.

2. The traditional theoretical framework for the consumer purchase decision

Since the 1960s, marketing science has produced a huge volume of literature on the various aspects of consumer behavior. Engel, Blackwell, and Miniard (1995) present the most recognized model of consumer purchase decision-making. This model divides the consumer purchase decision process into 5 stages: 1) problem recognition, 2) information search, 3) alternative evaluation, 4) purchase decision, and 5) post-purchase behavior. Fig. 1 shows this framework.

With the aid of this model, Engel et al. (1995) have also identified some factors that affect consumer purchase decision-making. These factors fall into three categories: 1) personal, 2) psychological and 3) social. The model provides an operational marketing management tool, while consumer behavior theory has become the most prevalent one in the marketing arena. However, so far researchers have published little literature on the question how these factors interact to form the inner psychological purchase decision-making process.

3. An agent-based model of the purchase decision-making process

3.1. Psychological theory of behavior and decision-making

Decision-making is a complex cognitive process involving perception, learning and information processing. As Engel et al.'s (1995) model (Fig. 1) shows, most of the consumers' purchases

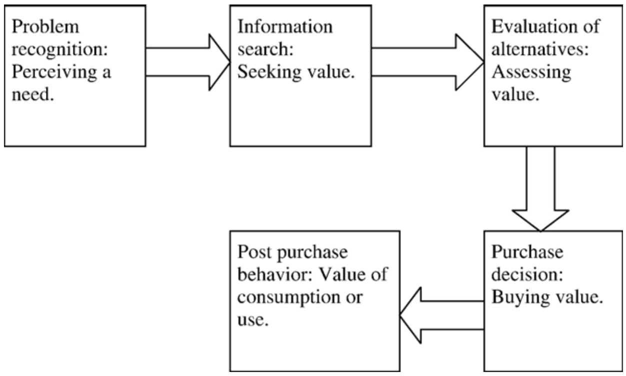

Fig. 1. Traditional theoretical consumer purchase decision model.

are planned behaviors. "A central factor in the theory of planned behavior is the individual's intention to perform a given behavior. Intentions are assumed to capture the motivational factors that influence a behavior; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior. As a general rule, the stronger the intention to engage in a behavior, the more likely should be its performance" (Ajzen, 1991, p181). The reasoned action model (Ajzen and Fishbein, 2005), as shown in Fig. 2, also suggests that intention is the immediate antecedent of actual behavior, influenced by a wide range of background factors. McClelland (1987) divides intentions into two categories: conscious intention and unconscious intention, while also suggesting that motivation is the reflection of conscious intentions formed by observing behaviors.

3.2. The purchase motivation model

Most of the purchase decisions are reasoned actions. Therefore, intention in the purchase decision-making process refers to conscious intention, and one can consider motivation as the direct determinant of the purchase decision. A method to discover motivation is to study what makes people reach logical decisions (McFarland, 1974). Based on marketing theory, the key stimuli that lead consumers to make their purchase decisions in the complex business environment are prices, quality, brands of products, advertisements, friends'/families' recommendations and disqualifications and consumers' previous purchase experiences. The consumer's personality traits determine how these external stimuli affect him/her. Ajzen (2005) defines personality as a characteristic of an individual that exerts pervasive influence on a broad range of trait-relevant responses. On this basis the consumer purchase motivation model consists of three parts: external stimuli, personality traits, and motivation (see Fig. 3).

3.3. The purchase decision model

Before constructing the model, the assumption has to be that consumers make purchases based on logical decisions, which is in line with the reasoned action and conscious intention theories. From this perspective, an individual consumer is an agent, and a group of artificial agents together with some brands within one particular product category form an artificial market. All agents have their own personality traits and their socio-economic interactions are based on their counterparts in the real market. In this virtual market consumer behavior depends on which brand an agent would choose, as shown in Fig. 4.

An agent has two types of interactions. One is the interaction between the agent him/herself and the brand managers. This type of interaction occurs in various forms of marketing activities. For example, interaction with respect to issues such as price, quality of the product, advertising, distribution channels, etc. The other type refers to the interactions among heterogeneous consumer agents. As Ben Said et al. (2001) indicate, the interactions among the consumer agents are based on recommendation or disqualification by family, friends or opinion leaders, or on rumors among the agent groups, etc. These two types of interaction are shown in Fig. 5.

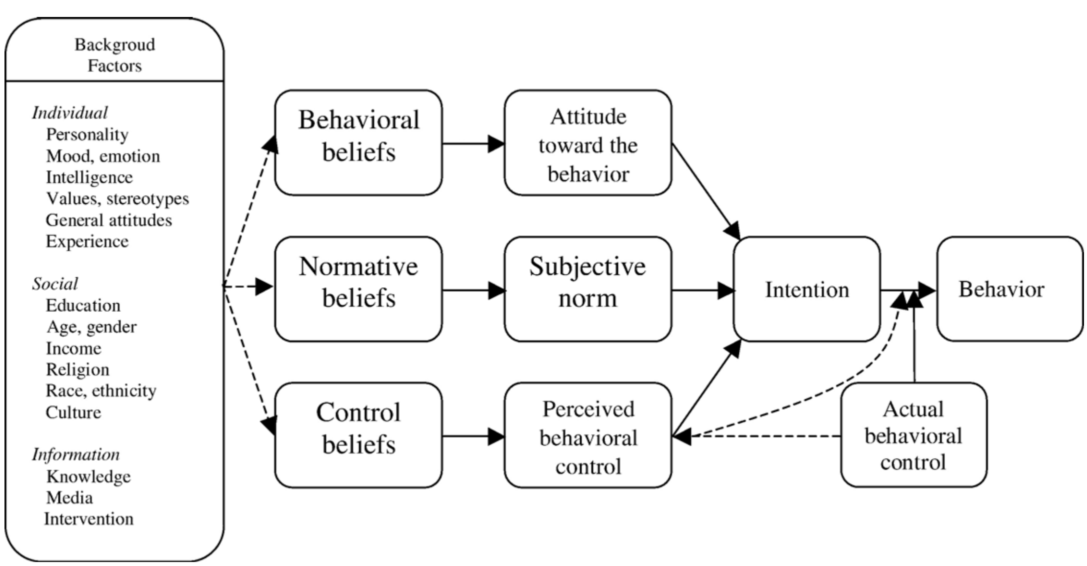

Fig. 2. The theory of reasoned action and planned behavior (Ajzen and Fishbein, 2005, p194).

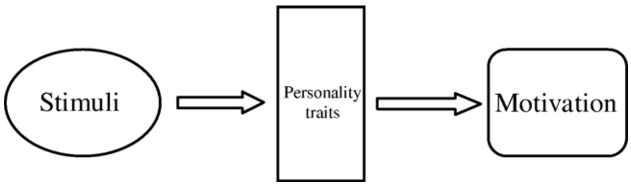

Fig. 3. Purchase motivation model.

The stimuli derived from the above two types of interaction have a great influence on the agent's motivation to buy the product. However, the agents' personality traits determine the stimuli's influencing powers, as the purchase motivation model in Fig. 3 shows. Therefore, based on the stimuli related to the two types of interactions, one can derive their relevant personality traits, namely price sensitivity, quality sensitivity, susceptibility, and follower tendency. Each stimulus' contribution to the agent's purchase motivation is calibrated by the agent's relevant personality trait. For example, if an agent is not price sensitive, then the price has little influence on his/her motivation to buy a product. Additionally, the agent's socio-demographic attributes, such as age, income, educational level, and professional status, may greatly influence the agent's personality traits. For instance, a millionaire might not think a £5 cake is expensive, whereas an unemployed person might think it is very expensive, because millionaires are less price-sensitive than the unemployed are. Due to the great influence of socio-demographic attributes upon the agent's personality traits, the purchase decision model has to take into account such attributes. Fig. 6 demonstrates the agent's purchase decision model.

3.4. The motivation function

As shown in Fig. 6, in the purchase decision-making process the external stimuli are the independent variables. Once an agent has perceived these independent variables, he/she will be psychologically processed in line with his/her relevant personality traits. After the processing, the agent has established a purchase motivation. With different choices, the agent will achieve different levels of motivation. The preferred choice is the one that can bring the agent the largest degree of motivation. Purchase decision-making is a cognitive process in which the stimuli and personality traits can be defined by certain algorithms. Suppose N brands of a product are present in the artificial market. If one considers the stimuli as independent variables, and the personality traits as the coefficients of these independent variables, the motivation function, which represents this algorithm, is as shown below:

$$M_i = \mathrm{PS}_i \times P_i + \mathrm{QS}_i \times Q_i + \mathrm{sus}_i \times \mathrm{ad}_i + \mathrm{ft}_i \times \mathrm{infl}_i \qquad (1)$$

M_i is the motivation brand i ($i=1$ to N) of a consumer agent. QS_i is the agent's quality sensitivity parameter to brand i; Q_i is the quality of brand i; sus_i is the agent's susceptibility parameter to brand i's advertisements; ad_i is the advertising intensity of brand i; ft_i is the agent's follower tendency parameter of the perceived influence exerted by other agents regarding brand i; infl_i is the perceived influence exerted by other agents with respect to brand i; PS_i is the agent's price sensitivity parameter to brand i; and P_i is the price of brand i.

3.5. Model calibration

In order to computationally simulate the decoy effect, the first step is to calibrate the motivation function, i.e. working out the detailed formula and setting the proper values of coefficients and parameters. In the first part of the motivation function, PS_i, the parameter of the personality trait price sensitivity, is the coefficient of the stimulus P_i. A Dutch psychologist, Peter van Westendorp, originally devised price sensitivity in the 1970s. Price sensitivity is an analysis of price elasticity based on the monetary, utilitarian, and emotional value that consumers attribute to a product or service. In this model, price sensitivity is one of the agent's personality traits and the model uses this concept to measure the degree to which price can trigger hindrance to an agent's motivation to buy a product. It is a negative figure because price definitely has an adverse effect on the purchase motivation. Each P_i can trigger a PS_i ($i=1$ to N) based on an agent's price sensitivity personality trait. The price sensitivity distribution model (Kim et al., 1995) suggests that the lower a brand's price, the less price sensitivity this brand

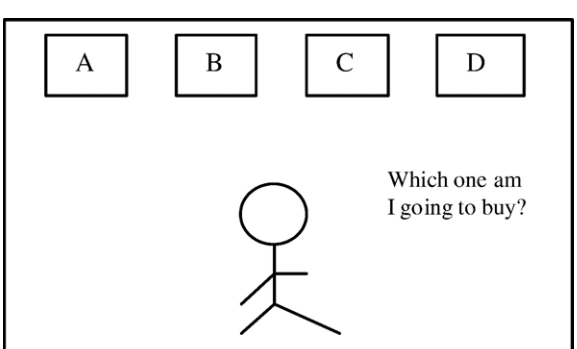

Fig. 4. Consumer behavior in an artificial market.

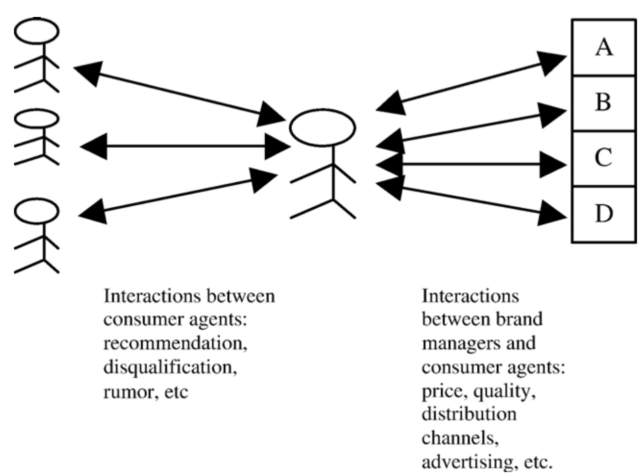

Fig. 5. An agents' two kinds of interactions.

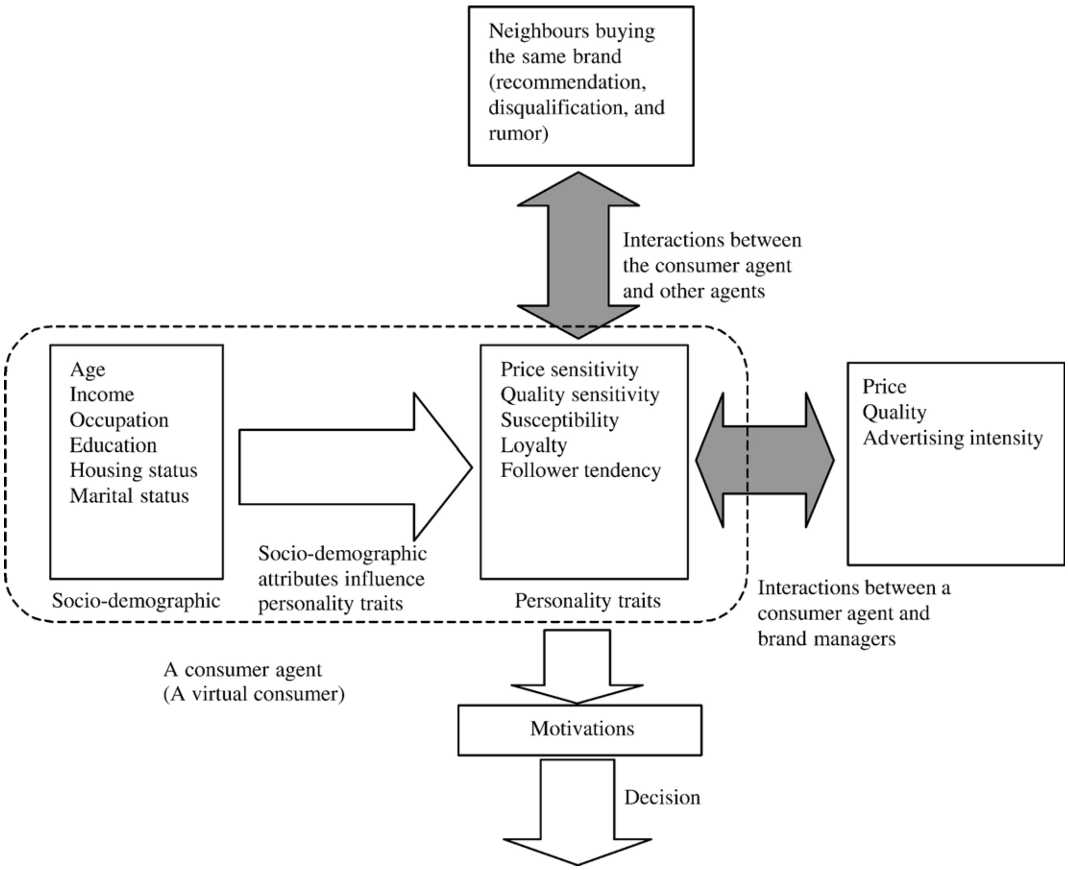

Fig. 6. The purchase decision model.

generates, i.e. the brand triggers less hindrance to an agent's purchase motivation. Kim et al's (1995) research also indicates that a consumer's price sensitivity is an exponential function of the difference between the real price of a product and the expected price of the product, as shown in Eq. (2).

$$\mathrm{PS}_i = -\alpha^{P_i - P_e} + k \tag{2}$$

where α is a parameter and $\alpha > 1$, k is a constant (the value of k is based on an agent's socio-economic attributes, e.g. millionaires are less price sensitive than unemployed persons) and P_e is the agent's expected price of this type of product. P_e is difficult to derive and can be substituted with the average price of the product, i.e. one can set:

$$P_e = P_{\mathrm{ave}} = \frac{1}{N}\sum_{i=1}^{N} P_i \tag{3}$$

where N is the number of brands of the product, P_i is the price of brand i, and P_{ave} is the average price of all brands of the product. Thus based on Eqs. (2) and (3), the result is:

$$\mathrm{PS}_i = -\alpha^{P_i - P_{\mathrm{ave}}} + k \tag{4}$$

Similar to the first part in the motivation function, QS_i, the parameter of the personality trait quality sensitivity is the coefficient of the stimulus Q_i. The psychological term quality sensitivity serves to measure the degree to which the quality of a brand can propel an agent's motivation to buy a product. In terms of quality, quality sensitivity is a multi-dimensional variable, because a brand may have qualities in different aspects, e.g. a mobile phone may be used to make calls, send text or picture messages and surf the Internet. Assuming brand i of a product has m qualities, then the overall quality of brand i in the model can be computed as:

$$Q_i = \sum_{j=1}^{m} W_j Q_{ij}$$

where Q_{ij} is brand i's quality j, and W_j, which can be used to measure how important Q_{ij} is to an agent, is the weight of Q_{ij}. The outlier avoidance consumer psychological theory (Patel and Schlijper, 2004) suggests that, when a consumer chooses a brand, the closer the quality of the brand approximates the consumer's expected quality of this kind of product, the more sensitive the consumer is to the quality of this brand. The mathematical formula is then:

$$\mathrm{QS}_i = \beta^{|Q_i - Q_e|} + L \tag{5}$$

where QS_i is the parameter of an agent's quality sensitivity triggered by brand i's quality Q_i, β is a parameter and $0 > \beta > 1$, and L is a constant (the value of L is based on an agent's socio-economic attributes). Consumer lifestyle research

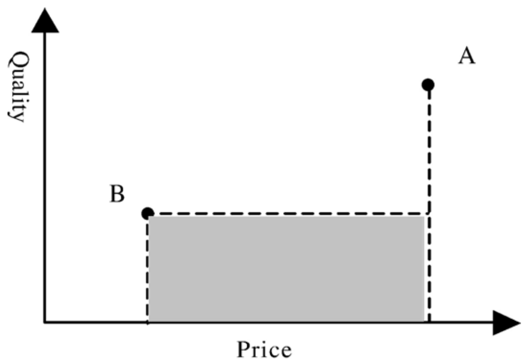

Fig. 7. Decoy effect.

carried out by Gardyn (2002) indicates that consumers from upper social classes pay more attention to the quality of the goods and services when making purchase decisions. Q_e is the agent's expected quality of this type of products, which one can substitute with the average quality of all brands of the product type, i.e. the formula is:

$$Q_e = Q_{\text{ave}} = \frac{1}{N}\sum_{i=1}^{N} Q_i \tag{6}$$

where Q_{ave} is the average quality of all brands of the product. Accordingly, based on Eqs. (5) and (6), this results in:

$$QS_i = \beta^{|Q_i - Q_{\text{ave}}|} + L \tag{7}$$

In accordance with the third and fourth part of the motivation function, an agent accepts the advertisement and influence from other people's stimuli, processes them and assigns psychological parameters to them on the basis of his/her personality traits, susceptibility and follower tendency. In order to highlight the price–quality trade-off during the decoy effect, this multi-agent simulation of the decoy effect bases the psychological parameters produced on the personality traits constants "susceptibility" and "follower tendency". Hence, the following two equations are obtained:

$$\text{sus}_i = \theta \tag{8}$$

$$\text{ft}_i = \lambda \tag{9}$$

where θ and λ are two constants.

Combining the Eqs. (1), (4), (7)–(9), the detailed formula of the motivation function is:

$$M_i = \left(-\alpha^{P_i - P_{\text{ave}}} + k\right) \times P_i + \left(\beta^{|Q_i - Q_{\text{ave}}|} + L\right) \times Q_i + \theta \times \text{ad}_i + \lambda \times \text{infl}_i$$

So an agent's final purchase decision is based on the algorithm:

$$\max\ \{M_1, M_2, M_3, \ldots, M_i\}$$

The brand that can bring an agent the largest degree of motivation is the agent's final choice.

4. Multi-agent simulation of the decoy effect

4.1. The decoy effect

If two brands of a product are available in a market, brand A and brand B, consumers have to make a choice between the two. If brand A has a superior quality but its price is much higher than that of brand B, consumers face a price/quality trade-off. If however, a third brand C (usually called a decoy), which is inferior to brand B in both price and quality, appears on the market, this may affect consumer choice. Various experiments have shown that, although no consumer will choose brand C (which is obviously inferior, as shown in Fig. 7), its mere appearance causes a substantial shift of preference from A to B. Marketing researchers call this effect the decoy effect. This effect is one of the most robust biases in consumer choice. Various product classes, ranging from chocolate bars or beer to TV-sets, have employed this instrument (Devetag, 1999).

In a famous study on the decoy effect, Huber, Payne, and Puto (1982) asked participants to choose between a five-star restaurant, which was a 25-min. drive away and a three-star restaurant, which was 5 min away. The subjective benefit of the five-star restaurant's better services is equal to the subjective benefit of the three-star restaurant's shorter driving distance. Two decoy experiments took place. When the researchers added a four-star restaurant with a 35-min. drive to the choice set as a decoy, the result showed that the participants tended to prefer the five-star restaurant that was 25 min away. However, when the decoy was a two-star restaurant 15 min away, the result showed that the participants' preferences had switched to the three-star restaurant 5 min away.

The Decoy effect illustrates the significant importance of consumer psychology, of understanding how consumers perceive products, and how consumers judge quality prior to purchasing the product (e.g. Doyle et al., 1999). This has long been of great interest to marketing scientists and psychologists. Min (2003) summarizes three types of decoy: an asymmetrically dominated decoy (Heath and Chatterjee, 1995; Huber et al., 1982), a phantom decoy (Highhouse, 1982; Pratkanis and Farquhar, 1992) and a compromise decoy (Simonson, 1989, 1992). Although these decoys differ in terms of their relationship with other options in a choice set of products, their availability and the underlying mechanisms proposed to account for their impact all have a positive effect on the target product (Min, 2003). The decoy effect mechanism has attracted the interests of many researchers and the explanation of this phenomenon is a big challenge. Many publications on the mechanisms and applications of the decoy effect have appeared since the 1980s, including comparison-induced decoy effects (Choplin and Hummel, 2005), loss aversion (Highhouse, 1982; Tversky and Kahmeman, 1991), attribute importance change (Huber et al., 1982), extending compromise effect models to complex purchase decisions based on the decoy effect (Kivetz, 2004), ease of justification (Park, 2005; Simonson, 1989; Wedell and Pettibone, 1996), and a no-numerical explanation (Quesada et al., 2005).

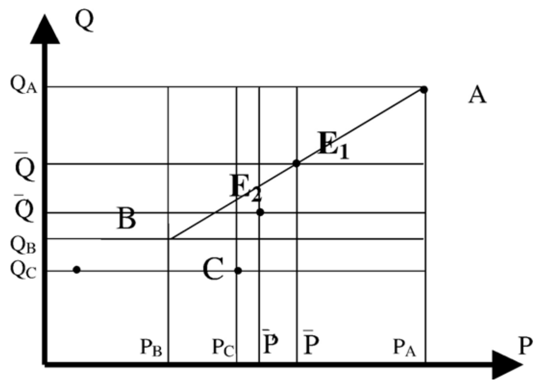

Fig. 8. The average points.

4.2. The mathematical analysis of an individual decoy effect

The nature of the decoy effect can be revealed by analyzing an individual consumer's motivation that changes from brand A to brand B after the introduction of the decoy. For example, consider a consumer whose initial choice is brand A, but the difference in his/her preferences for brands A and B is very small, i.e. $M_A - M_B = e$ where e is a parameter and is near 0. The smaller e is, the easier the consumer is affected by the decoy.

If dP is used to represent the difference between a brand's price and the average price of the product category, while dQ serves to indicate the difference between a brand's quality and the average quality of the product category, and M_A and M_B denote the consumer's motivations for brand A and B, one obtains the following equations:

$$\begin{aligned} dP_A &= P_A - P_{ave} \\ dP_B &= P_B - P_{ave} \\ dQ_A &= Q_A - Q_{ave} \\ dQ_B &= Q_B - Q_{ave} \end{aligned}$$

$$M_A = \left(-\alpha^{dPA} + k\right) \times P_A + \left(\beta^{|dQA|} + L\right) \times Q_A + \theta \times ad_A + \lambda \times infl_A \tag{11}$$

$$M_B = \left(-\alpha^{dPB} + k\right) \times P_B + \left(\beta^{|dQB|} + L\right) \times Q_B + \theta \times ad_B + \lambda \times infl_B \tag{12}$$

After the entry of the decoy, dP' and dQ' serve to denote the new difference between a brand's price and the average price of the product category and the new difference between a brand's quality and the average quality of the product category respectively. M_A and M_B, the consumer's new motivations for brand A and B, and ad'_A, $infl'_A$ ad'_B and $infl'_B$ serve to denote brands A and B's new advertising intensities and their influences on consumers. On this basis one obtains the following equations:

$$\begin{aligned} dP'_A &= P_A - (P_A + P_B + P_C)/3 \\ dP'_B &= P_B - (P_A + P_B + P_C)/3 \\ dQ'_A &= Q_A - (Q_A + Q_B + Q_C)/3 \\ dQ'_B &= Q_B - (Q_A + Q_B + Q_C)/3 \end{aligned}$$

$$M'_A = \left(-\alpha^{dP'A} + k\right) \times P_A + \left(\beta^{|dQ'A|} + L\right) \times Q_A + \theta \times ad'_A + \lambda \times infl'_A \tag{13}$$

$$M'_B = \left(-\alpha^{dP'B} + k\right) \times P_B + \left(\beta^{|dQ'B|} + L\right) \times Q_B + \theta \times ad'_B + \lambda \times infl'_B \tag{14}$$

By using Eq. (13) minus Eq. (11), and Eq. (14) minus Eq. (12), one obtains the following equations:

$$M'_A - M_A = \left(\alpha^{dPA} - \alpha^{dP'A}\right) \times P_A + \left(\beta^{|dQ'A|} - \beta^{|dQA|}\right) \times Q_A + (ad'_A - ad_A) \times \theta + (infl'_A - infl_A) \times \lambda \tag{15}$$

$$M'_B - M_B = \left(\alpha^{dPB} - \alpha^{dP'B}\right) \times P_B + \left(\beta^{|dQ'B|} - \beta^{|dQB|}\right) \times Q + (ad'_B - ad_B) \times \theta + (infl'_B - infl_B) \times \lambda \tag{16}$$

Eq. (15) minus Eq. (16) results in Eq. (17).

$$\begin{aligned} M'_A - M'_B = {} & \left(\alpha^{dPA} - \alpha^{dP'A}\right) \times P_A - \left(\alpha^{dPB} - \alpha^{dP'B}\right) \times P_B \\ & + \left(\beta^{dQ'A} - \beta^{dQA}\right) \times Q_A - \left(\beta^{dQ'B} - \beta^{dQB}\right) \times Q_B \\ & + (ad'_A - ad_A - ad'_B + ad_B) \times \theta \\ & + (infl'_A - infl_A - infl'_B + infl_B) \times \lambda + e \end{aligned} \tag{17}$$

Suppose E_1 is the quality–price average point before the entry of the decoy, and E_2 is the new quality–price average point after the entry of the decoy. Fig. 8 demonstrates their relationship.

Based on the properties of the exponential functions, one can analyze the result of Eq. (17). As shown in Fig. 9, $\alpha^{dP'A} - \alpha^{dP'A} > \alpha^{dP'B} - \alpha^{dPB} > 0$, and $P_A > P_B > 0$, therefore $(\alpha^{dPA} - \alpha^{dP'A}) \times P_A - (\alpha^{dPB} - \alpha^{dP'B}) \times P_B > 0$. On the other hand, with Fig. 10,

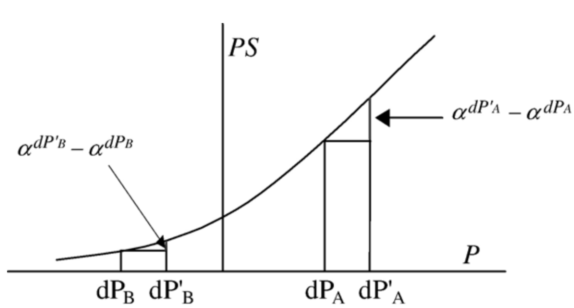

Fig. 9. The changes of price sensitivities.

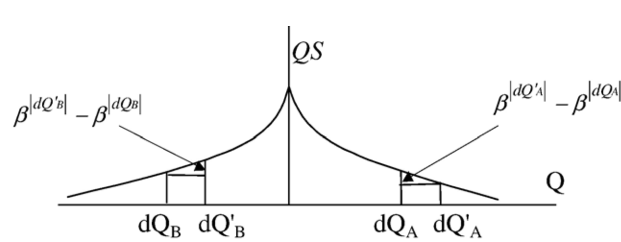

Fig. 10. The changes of quality sensitivities.

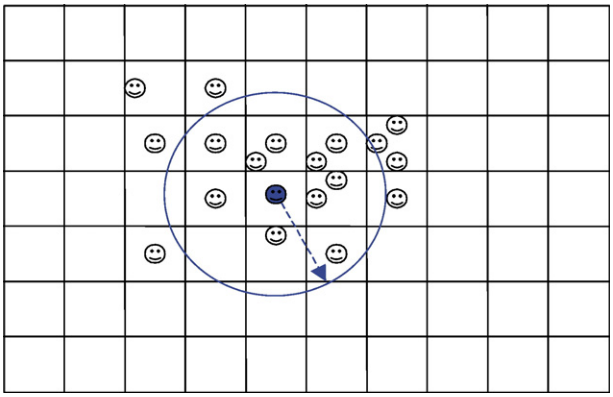

Fig. 11. Agents' distribution and interactions. Note: each agent is distributed in a grid, named a patch in NetLogo. In the simulation, each patch is the area where an agent lives. A grid may have no agents or more than one agent. The simulation assumes that an agent has interactions with other agents distributed less than 3 times radius away from where it stands. The larger the number of times radius, the more interactions an agent has. If the number of times radius is equal to the value of screen-edge-x, the simulation becomes a small world simulation as each agent fully interacts with all the other agents in the artificial market. Advertising intensity is randomly distributed, ranging from 0 to 100 in each grid. For details about patches, turtles, number of times radius and screen-edge-x, please see the Manual of NetLogo 3.0.2.

$\beta^{|dQ'A|;}-\beta^{|dQA|}>0$, $\beta^{|dQ'B|}-\beta^{|dQB|}>0$, together with $P_A>0$ and $P_B>0$, results in $(\beta^{|dQ'A|}-\beta^{|dQA|})\times Q_A-(\beta^{|dQ'B|}-\beta^{|dQB|})\times Q_B>0$. As the analysis focuses on an individual consumer's decoy effect, the model assumes that the decoy's entry does not mathematically change ad_A, $infl_A$, ad_B and $infl_B$ (i.e. a consumer who has been affected by the decoy would not exert influence on other consumers), therefore $(ad'_A-ad_A-ad'_B+ad_B)\times\theta=0$, and $(infl'_A-infl_A-infl'_B+infl_B)\times\lambda=0$. Moreover, as e is assumed to be near to 0, one can infer that Eq. (17) is less that 0, i.e.

$$M'_A-M'_B>0$$

Thus, from the initial $M_A>M_B$ to the current $M'_A>M'_B$, the consumer has shifted his/her preference from A to B.

Table 1
The scale and distribution of variables/parameters in the simulation

Variables/ parameters	Scale	Distribution
Income	0–1000	Random normal distribution, $\mu=600$ and $\sigma=75$
L	0–100	Depends on income
K	−100–0	Depends on income
ad	0–100	Random distribution
P_A	80–100	Random distribution
Q_A	80–100	Random distribution
P_B	0–20	Random distribution
Q_B	0–20	Random distribution
P_{decoy}	$P_B>P_{decoy}>P_A$	Random distribution
Q_{decoy}	$Q_{decoy}>QB$	Random distribution
Influ_out	0–100	Random normal distribution, $\mu=30$ and $\sigma=20$
sus_i	0–100	Random normal distribution, $\mu=55$ and $\sigma=20$
ft_i	0–100	Random normal distribution, $\mu=55$ and $\sigma=20$
A	$\alpha>1$	Depends on training and testing
B	$0>\beta>1$	Depends on training and testing

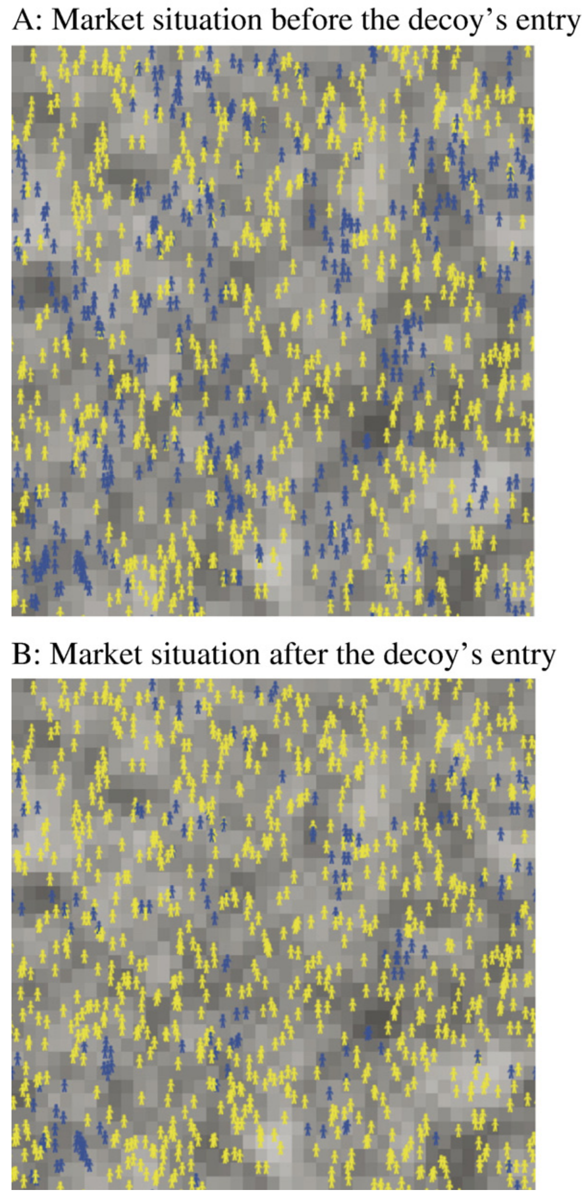

Fig. 12. Decoy effect: the market situation before and after the decoy's entry. A: Market situation before the decoy's entry. B: Market situation after the decoy's entry.

The mathematical analysis of an individual consumer's shift of preference is similar to the research on the decoy effect previously presented in key publications. Both focus on the aspect of an individual consumer's psychology and choice behavior. However, this static equation-based analysis includes many assumptions. For example, e is very small, and the entry of the decoy on the market does not change ad_A, $infl_A$, ad_B and $infl_B$. Additionally, mathematical analysis can only partially explain the decoy effect. For example, if the price of the decoy falls into the area between $\overline{P}$ and P_A, mathematical analysis can hardly confirm whether Eq. (17) is larger or smaller than 0, which causes uncertainty. Actually, the shift of an individual consumer's preference is not only an independent individual behavioral pattern, but also, and in some cases perhaps more so, a pattern strongly related to the sociology of consumer groups or networks, e.g. the actual

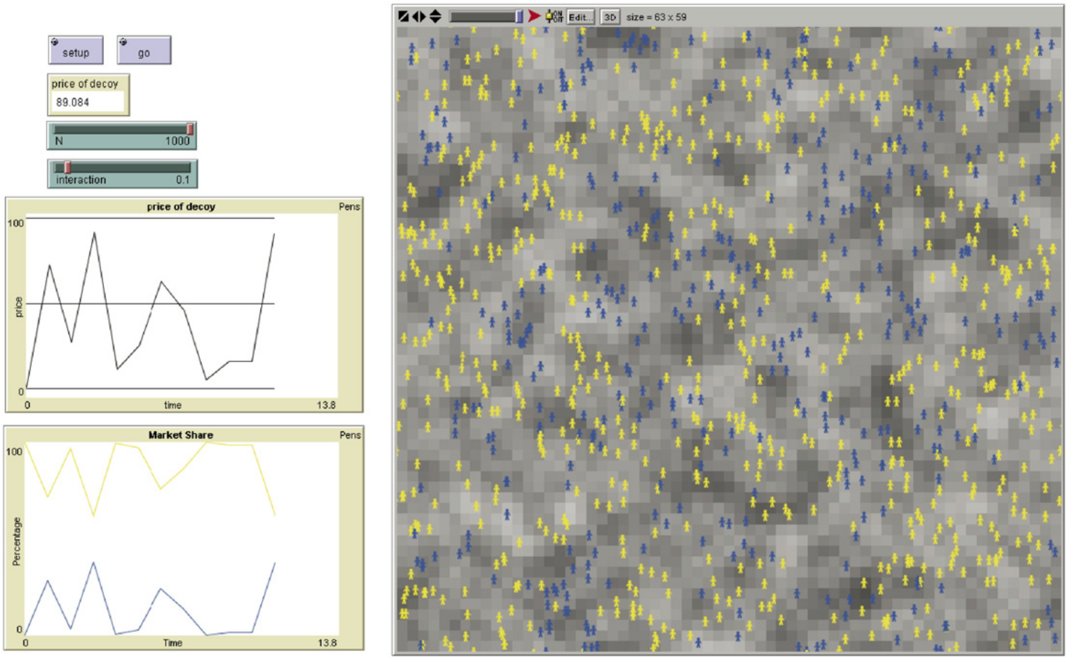

Fig. 13. The price of the decoy and market share.

situation in a real market is that the entry of the decoy on the market does change ad_A, $infl_A$, ad_B and $infl_B$. However, the static mathematical model reveals this dynamic process insufficiently. From a macro point of view, the decoy effect is a dynamically emergent marketing phenomenon that involves the preference changes of a large number of consumers and their sociological interactions. Therefore, although the decoy effect is not fundamentally the result of interactions, by using multi-agent computational simulation and taking into account the sociological interactions among heterogeneous consumers, one is capable of further exploring the decoy effect. However, until now little literature on computational simulation of the decoy effect has been presented. Based on the aforementioned agent-based purchase decision model, the authors exhibit the decoy effect dynamically by means of computational simulation.

4.3. The simulation

The authors programmed the motivation function with NetLogo 3.0.2. In order to reduce the complexity of the simulation in this virtual market, the authors used income to represent all of the agent's socio-economic attributes, e.g. age, housing status, and professional status. The simulation assumed the agents' incomes as ranging from 0 to 1000, normally distributed with $\mu=600$ and $\sigma=75$. Agents' price and quality sensitivity parameters ranged from 0 to 100 and were controlled by the constants k and L, on the basis of the agents' incomes; α and β were tested for and adjusted iteratively to model optimization. The constants θ and λ, (indications of the agents' personality traits susceptibility and follower tendency, normally distributed with $\mu=55$ and $\sigma=20$) ranged from 0 to 100.

The simulation distributed the artificial consumer agents randomly in different areas, and each consumer agent interacted with other agents distributed within X (X is adjustable) times of radius from where the agent was located (Fig. 11) The larger X, the more interactions the agent had.

In each area advertising intensity was randomly distributed, ranging from 0 to 100. The variable influ_out, normally distributed with $\mu=30$ and $\sigma=20$ and ranging from 0 to 100, represented an agent's influence on other agents, and another variable influ_in represented the influence an agent perceived from the other interacting agents. The simulation started from the assumption that an agent interacted with other agents distributed less than 3 times radius from where the agent was located, the value of the agent's influ_in being the sum of the values of these agents' influ_out. With more interactions in the simulation, the number of times radius increased, which appeared to make the model more complex. The random distribution of the price and quality of brand A was between 80 to 100, and the price and quality of brand B between 0 and 20. Table 1 shows the scales and distributions of the variables and parameters.

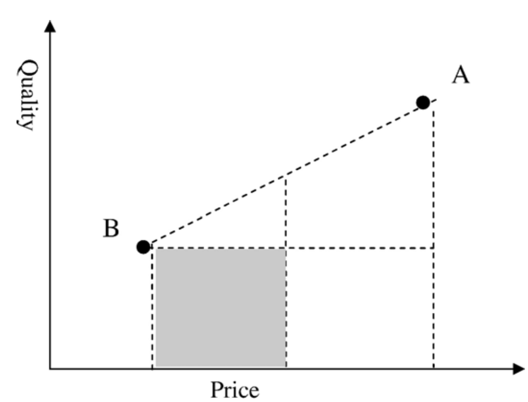

Fig. 14. Shaded area: best decoy area.

4.4. Experiment results

The simulation created an artificial market with 1000 consumer agents. The computer randomly picked up values of parameters and variables of each agent, based on the rules set in Table 1, which resulted in a high level of heterogeneity in the artificial market. The simulation results show that, at the entry of the decoy, the decoy effect was highly obvious. When the model ran one time step, the results were as shown in Fig. 12. Yellow agents were those who chose brand B, and blue agents were those who chose brand A. The decoy's entry on the market caused a substantial shift of preferences from A to B.

When checking the parameters of the agents who switched their preferences, the difference between their motivations for brand A (M_A) and their motivations for B (M_B) appeared to be very small. Thus, external stimuli easily lured these agents. Therefore, in practical marketing, changes in promotional tactics can easily influence this group of consumers. This finding is also in line with the assumption that e is very small in the mathematical analysis of an individual consumer's preference change. However, when checking the agents who never switched their preferences, the differences between M_A and M_B were very large, so these agents were either loyal to brand A or to brand B. Another discovery of the simulation was the best decoy area. When checking the decoy's price and market share, the results showed that whenever the price of the decoy fell into the area between brand B's price and the average price of brand A and B, i.e. $P_B > P_{decoy} > (P_A + P_B)/2$, the shift of the agents' preferences from A to B was very explicit. However, if $P_{decoy} > (P_A + P_B)/2$, the decoy effect becomes obscure. The price of decoy and market share curves in Fig. 13 demonstrate this. If marketers want to use the decoy effect in marketing, they can find a best decoy area based on the simulation (Fig. 14). This finding explains the uncertainty found in the mathematical analysis.

The authors conducted further research by changing the number of times of radius (from the default, which is 3), which can increase the value of influ_in (the influence that an agent perceives from other agents). The results show that the decoy had lured more agents, which indicates that, in a real business environment, intensive market competitions and word-of-mouth could decrease consumers' loyalty and make their behaviors more changeable and complex. In addition, the experimental results show that although the nature of the decoy effect is from the consumers' psychological perspective about price–quality tradeoff, which seems to be more an individual behavior than a group-collective behavior, the consumers' sociological interactions still account for a very important part of the decoy effect. If one sets the number of times of radius at nil (which means no interactions among the agents at all), the entry of the decoy only affects a few agents.

5. Conclusions

Compared with other research on consumer behavior, the agent-based model of consumer purchase decision-making and the multi-agent simulation of the decoy effect form a novel area in the multidisciplinary research that integrates marketing, psychology, sociology, engineering, and computer science. With respect to dynamically exhibiting and predicting market dynamics in a flexible manner, the traditional static equilibrium-based statistical and mathematical models lack robustness. The kind of computational simulation of consumer behavior presented here, however, has offered a new approach to fill this gap. The computational simulation is an effective novel business management tool. For example, this type of simulation enables one to conduct various experiments in the artificial market by changing the parameters to find out how a real market would respond to expected and unexpected events and to predict the evolution of this market. If the fidelity of the agents in the simulation is appropriate, the business information gained by this simulation technique will be much more accurate than that gained by traditional techniques, such as data mining.

Significantly, this research has also provided an example of a generic method for simulating other complex systems involving human beings, whose behavior is difficult to compute. Such complex systems include outlets, large supermarkets, political elections, complex manufacturing systems and even complex ecological systems. The steps in conducting this research are the following: 1) setting the simulation scope and defining the agents, 2) designing the proper algorithms based on the agents' counterparts in the real world to control the agents' behaviors, interactions and actions, 3) calibrating algorithms and models, 4) programming and running the model, 5) testing, validating and optimizing the model and, 6) observing and analyzing the experiment results. This research route can be referred to as a generic research method based on complex system simulation. The most important and difficult of the six steps is the algorithm design based on the agents' counterparts in the real world. The behaviors and actions of the objects in the real world may be very complex. If the algorithms are not designed properly, agent fidelity may be very low, which could hugely undermine the quality of the simulation results. Therefore, researchers should pay scrupulous attention to algorithm design.

6. Recommendation and further research

In this type of simulation an issue of debate is whether consumers' choices are rational. The answer may lie in the words of Dr. Bryan D. Gross (2004), President and Chief Executive Officer of MPSI Systems Inc. at a presentation at the London School of Economics. When questioned about this, Dr Gross replied: "We are all consumers. If we were behaving purely at random then our hypotheses would not enable us to predict consumer behavior. We might look at the numbers and say initially that as far as store location was concerned, consumers were behaving very randomly. But when we add the other factors and start partitioning up the variability we can actually see for example, that although location is a significant driver, consumers are making their decisions very logically. One of the things that we find is that consumers tend to switch on and switch off. We have an analysis that we do for price sensitivity and we see consumers switching on and off to price as a primary driver. That means that instead of a nice non-linear continuous curve we start to see discontinuities. But it's still very much the result of logical choice".

One limitation of the simulation is that the model ignores the self-learning ability of consumers. In the real world, consumers can proactively learn from the environment and gain experience. The experience accounts for part of the purchase decision. Another limitation of the simulation is that in order to decrease the complexity of the model, the researchers used income to represent all the agents' socio-economic attributes, including marital status, housing status and professional status. To a certain degree, this also decreased the degree of agent fidelity.

Further research will focus on these limitations, aiming at establishing an agent-based model of consumer behavior with an even higher degree of agent fidelity, and then upgrading this model to system level by using a multi-agent system to simulate another emergent lock-in market phenomenon.

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