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Original scientific paper

Modelling the Consumption Behaviour of Heterogeneous Consumers: A Duty-Free Shop Case Simulation Analysis

Yue LIN, Dan CHANG*

Abstract: Duty-free shops, which have emerged in major airports, first-tier cities, free trade zones and other places, have become ideal places for not only facilitating people to buy goods but also promoting the development of the local economy, which makes the study of the heterogeneous consumer purchase behavior in duty-free stores of great importance and great practical significance. Based on this, the agent model is used to study the purchase behavior of heterogeneous consumers in duty-free stores, the structure of the agent model is proposed, the consumer submodel and situation submodel are designed, and a service recommendation is made. On this basis, the consumer behavior is simulated and analyzed both with and without considering situational factors. The following conclusions are drawn: (1) The display, the month, holidays, and other factors have an important impact on the heterogeneous consumers of duty-free stores and affect consumers' consumption behavior. (2) Salespeople's recommendation rules and consumers' purchase preferences affect consumers' purchase behavior, which has an important impact on the types and quantity of goods consumers buy.

Keywords: agent model; duty-free shop; heterogeneous consumers; purchase preference

1 INTRODUCTION

There are many factors that influence consumer buying behavior, and consumer preferences and the salesperson's recommendations are among the key influencing factors. Preference is a multidimensional concept that includes cognitive, behavioral and emotional preferences. Consumer attitudes and behaviors can differ depending on consumer preferences, i.e., consumer preferences are different, undoubtedly presenting a challenge for the development of various sales activities. In terms of business practice, the key to standing out in a competitive market is to have a clear understanding of the differences between consumer preferences and to be able to make recommendations to meet the needs of different consumers according to their preferences. In terms of academic research, it is important to precisely understand the consumer preferences of different consumers and to obtain information about the process of the formation and development of consumer preferences. Currently, most scholars use agent modeling to analyze consumer preferences. Agent-based computational marketing is a cross-discipline between computational economics and marketing, and the modeling approach does not adopt the fully rational view of individuals in classical economics but rather a finite rational agent, which encompasses both the characteristics of individuals and the interactions between them. Because of the active nature of each subject and its ability to adapt and learn from its environment, the method facilitates the study of complex systems and is increasingly being used in the social sciences based on agent modeling. Currently, the approach focuses on three main areas of consumer behavior research.

The first area is the study of agent-based consumer heterogeneity. Agent-based modeling approaches are characterized by individual heterogeneity and thus can explain heterogeneous consumer behavior from an individual perspective. Berger et al. [1] constructed a consumer simulation model to demonstrate the evolutionary process of consumer heterogeneity under artificial conditions, where consumer heterogeneity is manifested in the learning or communication process of the subject. Doniec et al. [2] conducted a simulation experiment on the evolution of consumer behavior using optimistic, pessimistic and innovative self-perception attitudes and imitation and reasoning. Chernev et al. [3] performed a simulation experiment on consumer behavior using the socialization processes of repetition, deep thinking, imitation and social comparison. Jin Chun et al. [4] argued that consumers go through a process of complex thinking to make purchase decisions, and they applied an agent modeling approach to analyze consumer purchase behavior and proposed different promotional strategies in different contexts. Wu J H et al. [5] used the agent modeling approach to divide the consumer's consumption process into four stages, namely, evaluating emotional persuasion behavior, updating emotional persuasion status, adjusting emotional persuasion goals and generating emotional persuasion behavior, and proposed an agent-based decision process model for emotional persuasion based on the characteristics of each stage.

The second area is the study of agent-based intersubject interaction approaches. Because of the effectiveness of agent-based modeling approaches for subject interaction, this approach is superior to other modeling approaches for studying the complexity of the performance level of consumer group behavior. Haynes [6] used an agent model to study how consumers are influenced by the diversity of information about goods, where consumers' consumption decisions are influenced by factors such as their family, friends, or holidays. Schlereth et al. [7] argue that differences in the form of interaction between consumers and sellers, as well as differences in access to product information, can affect consumers' consumption perceptions. Xiaochao Gu et al. [8] studied the influence of social network structure on the system based on the agent model. They compared the difference in the influence of the interaction mode between small-world network and scale-free network on the evolution of the market, and concluded that the opinion leader (OPINION LEADER) in the same group has an influence on the consumer's consumption decision. He Qi et al. [9] conducted a simulation experiment using word-of-mouth interactions to investigate the process of consumer acceptance of a brand.

The third area is the study of 'emergence' at the macro level of the agent. The concept of "emergence" is the core concept of the model, where macrolevel laws are formed by the interaction of microlevel subjects, changes in the macrolevel economy affect the behavior of microlevel subjects, there must be a specific relationship between the two, and the interaction of microlevel subjects finally leads to the conclusion of macrolevel "emergence" (Zhang Hao et al. [10]; Diehl et al. [11]). The simulation findings of Kan H. S. et al. [12] suggest that consumers have "lock-in" behavior toward a brand, i.e., consumers initially have a better experience with a brand and are not inclined to use another brand, even if the goods of the new brand provide a better experience, and the findings of this study have implications for how companies can maintain brand loyalty. Rodriguez et al. [13] studied the influence of social reputation on individual consumers' choice process based on the agent model and conducted a simulation experiment; Wu et al. [14] studied the influence of collective identity on individual consumer choice based on the agent model and conducted a simulation experiment. From a macro perspective, their findings are useful for understanding the formation and evolution of aberrant consumption behaviors such as conspicuous consumption and herd consumption in society.

With the development of the social economy and the extension of customs unions and free trade, there is an increase in the number of duty free shops, which provide people with an ideal shopping experience. Because of their special policy conditions and price advantages, duty-free shops have attracted a large number of consumers and have brought major profits. However, no research has yet focused on the purchasing behavior of consumers in duty-free shops, especially to answer the question of how consumers with different characteristics prefer to buy in duty-free shops. Furthermore, how do these purchasing preferences influence consumer behavior? Addressing these questions will help to provide a clearer understanding of heterogeneous consumer buying behavior in duty-free shops. Based on this, this paper adopts an agent-based simulation modeling method to find multiple service sales criteria by analyzing micro details such as consumers and shopping situations, taking personalized product recommendations in duty-free shops as an example, in order to realize a simulation experiment on the purchasing behavior of heterogeneous consumers in duty-free shops and provide a theoretical basis for duty-free shops to formulate different marketing strategies in response to different consumption needs of heterogeneous consumers.

The structure of this paper is as follows: the first part is the introduction. This part expounds the application of the agent modeling method on consumer behavior research, and it puts forward the purpose and significance of this paper. The second part is the construction of the agent-based heterogeneous consumer purchase preference model of duty-free stores, including the characteristics and model structure of the agent-based model simulation, as well as the consumer submodel and the situation submodel. The third part is service recommendation and consumer selection rules. This part involves the structure of service recommendation and consumer selection rules, the set of salespeople's recommendation rules, and the decision-making rules of consumers. The fourth part is a simulation analysis. Taking a duty-free store in Beijing airport as an example, the agent simulation model is used to simulate and analyze the personalized purchase preference of consumers and the promotion effect of salespeople to analyze the behavioral laws of heterogeneous consumers' purchase preferences in duty-free stores. The fifth part consists of the research conclusions: based on the simulation research, the research conclusion of this paper is put forward. The framework of this paper is shown in Fig. 1.

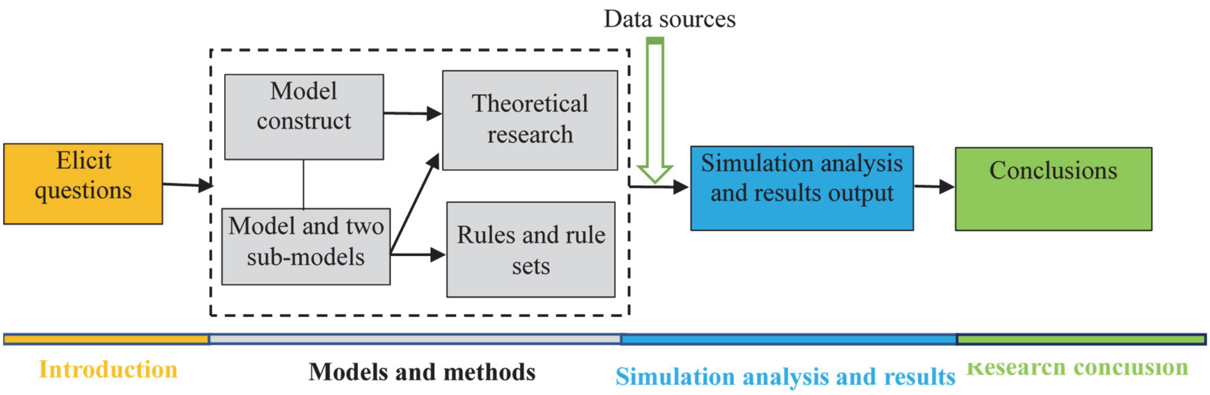


Figure 1 Research framework of the paper

2 MODEL CONSTRUCTION

2.1 Features of Agent-based Model Simulation

Compared to traditional marketing models, the agent-based modeling approach has three characteristics when modeling consumer behavior.

(1) The agent-based modeling approach makes more relaxed assumptions about the system and better reflects real-life consumption behavior. First, unlike top-down systems (top-down model), which have more stringent requirements of linearity and equilibrium, dynamic behavior usually emerges in an unbalanced environment during the operation of the model (Kim et al. [15]). Second, agent-based modeling takes into account consumer heterogeneity and limited rationality, although traditional models also take into account the former but more often only model consumer heterogeneity from an aggregate perspective and less often from an individual perspective.

Agent-based modeling can be used to classify different types of consumers in different ways, and consumers have the ability to learn and change their behavior through their past experiences, usually by "preferences", "herding" and other characteristics. These characteristics show the individual differences between consumers and the adaptability of consumer behavior.

(2) The agent-based modeling approach has good intraindividual interactions. The most obvious difference compared to traditional modeling methods is that the model allows for intraindividual communication mechanisms, which enable individuals to communicate and share information, for example. Agent-based modeling improves the shortcomings of individual subjects in the operation of the model by building an artificial virtual environment in social networks where individuals can change their behavior by observing changes in the real-time environment, and the display of consumer group behavior is more complex in the whole system than simply the accumulation of individual behaviors (Park et al. [16]).

(3) The complexity of the group emerges automatically (emergence) as a result of the bottom-up modeling concept. The underlying philosophy of agent-based modeling is bottom-up modeling, i.e., specifying the characteristics and behavioral rules of individuals rather than the whole. It can be argued that the trends of the overall system in the simulation process of the model evolve spontaneously from a certain point of view, and therefore researchers find some patterns in the existence of real-life consumer behavior when observing the simulation process of the agent model (Moerland et al.[17]). In addition, from a technical point of view, the agent model is easier to maintain and refine, with an unlimited number of system runs and the ability to add different types of individuals or different attributes of individuals at will during the run without damaging the starting state of the system, which is in line with changes in the real consumer market (Esteban et al.[18]).

2.2 Structure of the Model

Existing research on purchasing behavior has focused on five manifestations of consumption preferences, including but not limited to risky consumption preferences, value preferences, transactional behavior preferences, convenience preferences and relationship preferences. However, as most of the studies imply a basic premise that a consumer's consumption preference remains the same within a certain period of time, most of the literature focuses on the classification of consumption preference types to characterize consumption behavior, and few scholars and literature have studied the essential attributes and changes between consumption preference and consumption behavior in depth. To explore the essential connection between consumption preferences and consumption behavior, this paper takes the consumption scenario in a duty-free shop as an example to conduct a simulation study. The consumption activities in duty-free shops involve many objects, which are categorized and introduced into the following conceptual model (Fig. 2). The specific objects include the consumer as the subject of the activity, the salesperson as an auxiliary consumer, the goods as the object of consumption, and a series of contexts, including the place and the consumer's financial resources. In this model, it is argued that the purchase of goods in duty-free shops is not entirely determined by previous consumption preferences but rather by a certain randomness and that each consumer has a corresponding type of consumption preference.

In addition, the basic premise of the model is that (1) depending on the requirements of the duty-free shop, the promoter will focus on certain items; (2) members registered in duty-free shops have their purchase information and consumption preference information recorded in the shop; and (3) there are a certain number of brands and quantities of each product. (4) Consumers are not restricted in their choice, and their consumption activities are somewhat random. (5) The recommendations of specific products by the service staff in duty-free shops vary based on the value and quality of each type of merchandise.

Because of the intelligence, complexity and autonomy of the context, the consumer and the salesperson in this model, these three entities are modeled using the agent simulation, while the goods are used as a general object of study.

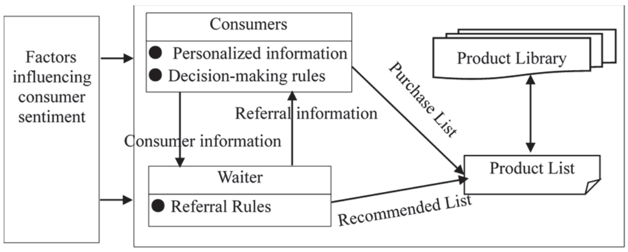


Figure 2 Conceptual model of consumer behavior and product recommendations in duty-free shops

2.3 Consumer Submodel

To recommend the best products to the consumer, information about the consumer's purchasing behavior is filtered, and then the agent model is used to simulate the consumer's consumption behavior and provide personalized recommendations. It is important to note that each group of consumers is characterized by each consumer agent, and there are many factors that influence consumer purchasing behavior, including but not limited to age, education, financial resources, job, family situation, product performance, etc. The characteristics of the filtered consumer buying behavior are summarized in three areas: recommendation acceptance rate, basic information and preference information. The basic information is characterized by the type and number of consumers, while the preference information is characterized by whether the consumer has a brand preference and whether the consumer has a category preference.

(1) Type of consumer $(c-type)$.

The types of consumers we define include casual customers who visit duty-free shops and members who are registered with duty-free shops, who can be divided into five levels: regular, silver, gold, platinum and diamond, and can therefore be defined as $c-type=\{C_1,C_2,C_3,C_4,C_5,C_6\}$. By classifying the types of consumers, we can abstract the characteristics of each type of consumer, such as age, financial resources, work, etc.

(2) Number of consumers $(c - num)$.

There is no direct relationship between the number of people consuming and the volume and type of goods sold, so for the purposes of this study, the paper divides them into five groups: more, more, moderate, less and less, characterized by $A = \{VS, S, MM, B, VB\}$.

(3) Product type preferences $(category)$ and product brand preferences $(brand)$.

The types of goods sold in duty-free shops are generally grouped into three categories, namely, luxury, premium and general products, which are now characterized at $Ca=\{C_{a1}, C_{a2}, C_{a3}\}$. Additionally, these goods are now classified into four brands, which are characterized as $Br=\{B_{r1}, B_{r2}, B_{r3}, B_{r4}\}$. In addition, we assume that there are 10 items of each brand in each category, assign them numbers from 1 to 10 and then characterize their consumer preferences in terms of likes and dislikes, which can be expressed as follows:

$$\begin{cases} category = < c_1, c_2 >, brand = < b_1, b_2 > \\ c_1, c_2 \in (D \bigcup \{non\}) \\ b_1, b_2 \in (Br \bigcup \{non\}) \end{cases} \tag{1}$$

In the above equation, type preference is characterized by c_1, c_2 and brand preference is characterized by b_1, b_2.

(4) Recommendation acceptance rate by consumers (*rate*).

Each customer has a different level of reaction and acceptance of the product marketed by the salesperson, and this behavior is portrayed in this study using the recommendation acceptance *rate*, where the size of the *rate* value reflects the level of acceptance of the product marketed by the customer.

From the above analysis, it is clear that information about a consumer's consumption behavior can be characterized as:

$$\Omega = \langle c\text{-}type, c\text{-}num, category, brand, rate \rangle \tag{2}$$

2.4 Contextual Submodel

There are many situational factors that influence customers' purchasing behavior, including personal financial resources, promotional discounts at duty-free shops, places of consumption and the occurrence of holidays. In our model, we focus on the influence of places of consumption, consumers' financial resources and the occurrence of holidays on the purchasing behavior of consumers.

$$\begin{cases} \Psi = \langle place, wealth, holiday \rangle \\ place \in \left(pl = \{airport, domestic, abroad\} \right) \\ wealth \in \left(we = \{VB, B, MM, S, VS\} \right) \\ holiday \in \{0,\ 0.5,\ 1\} \end{cases} \tag{3}$$

To stimulate tourism spending, duty-free shops are usually set up on land, at seaports and at airports. This paper focuses on duty-free shops set up at airports, and some duty-free shops are also permanently located in core areas at home and abroad, so they are also included in our study of key locations $Pl = \{airport, domestic, abroad\}$. Consumer affordability is a measure of consumer purchasing power, which determines the amount and type of consumer purchasing behavior. In this paper, consumer affordability levels are grouped into five specific groups: more, slightly more, moderate, less and much less, as characterized by $we = \{VB, B, MM, S, VS\}$. The number of consumers and the number of purchases increase significantly during the holiday season, which is the peak period for consumer purchasing behavior, and are grouped and assigned a value of 0 for weekdays, 0.5 for general holidays and 1 for important holidays.

The scenario submodel realizes personalized recommendations based on different contexts, and its stimulating effect on consumption is manifested in the following ways: different locations of duty-free shops lead to different types and quantities of products sold and therefore attract different types of consumers; the financial situation of consumers affects the categories and brands of products purchased by consumers, and generally speaking, consumers with greater financial resources are more likely to choose luxury and high-end products, while those with fewer financial resources generally choose ordinary products or products with a higher value for the money. Whether it is a holiday or not and the importance of the holiday will stimulate customers' consumption psychology and thus trigger their consumption behavior.

3 SERVIVE RECOMMENDATIONS AND CONSUMER CHOICE RULES

3.1 Structure of the Rules

Based on the analysis of consumer information, one can predict individual consumer preferences and their likely behavior and then make them a recommendation based on specific contextual influences, which is the purpose of recommendation. The recommendation mechanism can be structured in various ways, whether it is a set of rules, a decision tree, or the assignment of different weights to different feature vectors (Chun Jin et al. [19]; Bolzern et al.[20]).

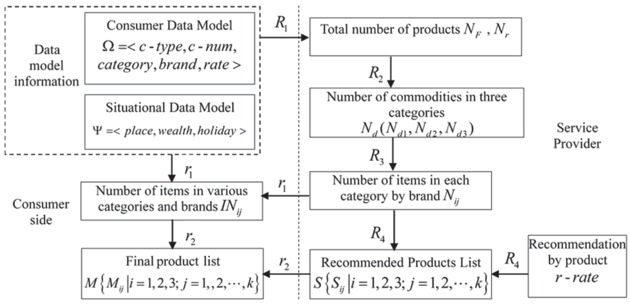


Figure 3 Flow chart of recommendation and decision rules

Guided by the rule-based approach, the consumer submodel and the contextual submodel were established in this paper, which in turn established the recommendation rules in this paper, as shown in Fig. 3. Fig. 3 shows the corresponding flowchart for service recommendation and consumer decision making, which reflects the specific rules applied to each stage.

3.2 A Collection of Referral Rules for Salespeople

The first is the rule for determining the total number of products to be recommended R_1, the second is the rule for determining the number of products to be recommended in three categories (luxury, premium and general) R_2, the third is the rule for determining the number of brands to be recommended in each of the three categories R_3 and the last is the rule for determining the specific products of each brand in each category. The last rule is the recommendation rule used to determine the specific product of each brand in each category R_4 and is referred to in the form of a collection of the four types of rules mentioned above, i.e. $R=\{R_1, R_2, R_3, R_4\}$. According to the flow chart in Fig. 2, from the salesperson's point of view, the personalized information and contextual information collected by the consumer will first be applied to the first category of rules, and the conclusions drawn from this will be an objective prerequisite for the application of the latter rules. As the four categories of rules progress in turn, the list of products that the salesperson decides to recommend is created. These four types of rules are described in detail below.

(1) Rules on the total number of recommended products R_1.

In addition to the number of consumers and the total amount of goods purchased, contextual factors such as consumer type and the occurrence of holidays can also have an impact on the total amount of goods purchased. If all other influencing factors are held constant, then assigning different values to the contextual attributes of holidays will have a different impact on the actual total amount of goods purchased by consumers, which, when combined with the previous analysis, can be expressed by the following equation R_1.

$$R_1 : c\text{-}num \wedge c\text{-}type \wedge holiday \rightarrow N_F \tag{4}$$

In Eq. (4), the total number of fuzzy products recommended will be referred to by N_F. Since the number of consumers is categorized in this paper based on a fuzzy aggregation, the same aggregation should be used for the total number of products, i.e., $F=\{VS, S, MM, B, VB\}$. For example, if the number of consumers is medium, the type of consumer is a regular member and the context is nonholiday, then the probability of the fuzzy set F_i for the total number of products recommended in this context can be expressed as $P=\{P_i \mid i=1, 2, ..., 5\}$. Eq. (5) is the corresponding specific rule expression.

$$\begin{aligned}&\text{if } (c\text{-}num \text{ is } MN \text{ and } c\text{-}type \text{ is } C_2 \text{ and holiday is } 0).\\&\text{Then } P(N_F = F_i) = P_i\end{aligned} \tag{5}$$

In the above equation, i =1, 2, ..., 5 and $P(N_F = F_i)$ refer to the probability that the total number of items recommended is the fuzzy value F_i.

If N_r is used to denote a specific quantity of a good, and $x \in V$ is used to denote a specific range of values for that quantity, where $V=\{2, 3, ..., n\}$, and $\mu_{F_i}(x)$ is used to refer to its corresponding subordinate function, the expression for N_r is shown in Eq. (6), which shows that N_F can be transformed into N_r after the defuzzification process.

$$N_r = \int_v \mu_{F_i}(x) x \mathrm{d}x \,/ \int_v \mu_{F_i}(x) \mathrm{d}x \tag{6}$$

(2) Rules on the number of recommendations for the three categories of products R_2.

The total number of items recommended and the consumer's preference for a particular type of item jointly determine the number of recommendations made by the salesperson for each type of item. In addition to these two aforementioned factors, the wealth level of the consumer is also an important factor in the number of items recommended. For example, this study concluded that consumers who are very wealthy or extremely wealthy are the main buyers of luxury jewelry goods, while consumers in other categories have less purchasing power for luxury jewelry goods, especially those with little wealth, who have almost no spending power for luxury jewelry goods. Therefore, in this case, the proportion of recommendations made by salespeople for the three categories of goods will vary, i.e., as shown in rule R_2.

$$R_2{:}N_r \wedge category(c_1,c_2) \wedge wealth \rightarrow N_d\left(N_{d1}, N_{d2}, N_{d3}\right) \tag{7}$$

In Eq. (7), the number of recommendations for each of the three categories is represented by N_{d1}, N_{d2} and N_{d3}, while the proportion of the number of items in category i to the total number of items is represented by the probability P_{di}.

(3) Rules on the recommended number of items of each brand in the three categories R_3.

The number of recommendations for a particular category of goods and the consumer's preference for that category of goods can jointly determine the number of recommendations for each brand of goods in the three categories, but of course, this value can also change depending on the venue. For casual customers and regular club members, consumers tend to choose luxury and high-end goods in foreign countries or airports and prefer to buy ordinary goods in China. However, Platinum and Diamond members are more inclined to choose luxury goods, both at home and in foreign locations. Therefore, the corresponding recommendation rule for R_3 is:

$$\begin{aligned}&R_3{:}N_{di} \wedge place(airport, domestic, abroad) \wedge\\&\wedge category \rightarrow N\left(N_{i1}, N_{i2}, N_{i3}\right)\end{aligned} \tag{8}$$

In Eq. (8), N_{ij} is the number of items of the brand j in the recommended category i. Similar to the rule above, the probability P_{ij} refers to the proportion of items of each brand.

(4) Rules for recommending specific products of each brand in each category R_4.

Based on the model assumptions in the previous section (5) and the design of the product library, the paper makes the assumption that if an item is of the same category and belongs to the same brand, the salesperson will recommend it more strongly if it has a smaller number. $rate(1) > rate(2) >, ..., > rate(k)$. In addition, as some specific items are limited edition items, the strength of recommendation (*r-rate*) and consumer preference for different limited edition items will vary greatly from one type of duty-free shop to another, meaning that the duty-free shop context will influence the final recommendation by affecting the limited edition items. Based on this, the following formula can be used to express the rule R_4.

$$R_4{:}N_{ij} \wedge rate \wedge place \rightarrow S\left\{S_{ij} \,|\, i=1, 2, 3; j=1, 2, ..., k\right\} \quad (9)$$

In the above expression, S_{ij} indicates the recommended combination of categories for the j branded item of category i, which will be replaced by the item number.

3.3 Decision Rules for Consumers

The first item that must be determined is the number of products of each brand in each category r_1, and the next is the final list of products r_2, so that the set of decision rules is represented as $r = \{r_1, r_2\}$ As seen in Fig. 2, the personalized information received by the consumer, the salesperson's recommendation of the product and the consumer's current situation all influence the decision he or she makes. The sequence of these two rules results in the consumer's list of products to purchase.

(1) Rules for consumers to determine the quantity of various types and brands of goods r_1.

After the salesperson has recommended a product to the consumer, the consumer will first take into account a certain amount of variation V_{ij} (the probability value achieved in the simulation is $P_{V_{ij}}$) in the number of different brands N_{ij} recommended by the salesperson, based on his or her personalized preference information I and his or her current situation W, to determine the number of different brands IN_{ij} that he or she finally decides to buy. In this case, the expression of rule r_1 is presented as:

$$r_1{:}I \wedge W \wedge N_{ij} \rightarrow IN_{ij} \quad (10)$$

(2) Decision rules for the final list of goods purchased by consumers r_2.

The consumer has the right to choose whether to accept or reject any of the items in the list of brands recommended by the salesperson at S_{ij}. This probability can be expressed at *rate*. After the initial determination of the combination of items to be purchased at S'_{ij}, the number of items to be purchased at this point is recorded. If $N'_{ij} N'_{ij}$ is greater than the number of items of a particular brand in this category previously decided by the consumer at IN_{ij}, the final list of items to be purchased by the consumer at M_{ij} is made up of an arbitrary selection of items from S'_{ij} in the number of items at IN_{ij}. If N'_{ij} is smaller than IN_{ij}, then the list of products that the consumer decides to buy is a combination of $\left(IN_{ij} - N'_{ij}\right)$ and S'_{ij} from a brand of products that the salesperson did not recommend. The acceptance rate of *rate* for the products recommended by the salesperson may vary depending on the situation of the consumer, which is rule r_2, expressed as follows:

$$r_2{:}rate \wedge S \wedge IN_{ij} \wedge place \rightarrow M\left\{M_{ij} \,|\, i=1, 2, 3; j=1, 2, ..., k\right\} \quad (11)$$

In Eq. (11), M_{ij} refers to the consumer choice mix of the i category of the j branded item, which is also represented by the item number, similar to the previous section.

4 SIMULATION ANALYSIS
4.1 Interaction Process Design

Interaction process design is the core of the model design. The consumers' consumption situation, their behavioral response pattern and the salesperson's sales pitch are all carried out in the interaction process (Sun, Dandan et al. [21]). Therefore, in this paper, based on the abstract analysis of consumers' consumption activities in duty-free shops and the sales promotion process of the salespeople, an agent customer behavior and sales promotion interaction flow chart is established, as shown in Fig. 4, which has three main stages in the life cycle of the interaction: the generation period, the operation period and the release period.

This paper uses JAVA programming to build the model through the multiagent simulation platform REPAST (Simphony) software. The model consists of two main libraries: an entity library, which is able to generate consumer data streams by the pattern and manner in which consumers arrive at the service platform, which can conform to a variety of distributions, as well as generating information on the external influences on the consumer's context and generating a corresponding rule base for the agent attributes of the consumer and the salesperson. The second is the function library, which is responsible for setting and adjusting the parameters of the model, generating visual 2D images of the model, and running and stopping the model.

This paper takes a duty-free shop in Beijing Capital Airport (which supports online shopping) as an example and simulates and analyzes the personalization of consumer behavior patterns and the effectiveness of salespersons' promotions through an agent simulation model. The relevant consumer data in the simulation model, such as basic consumer information, their current situation, their preference status and acceptance rate, are all set through the results of field research. The number of consumers received by the duty-free shop in a certain period was set at 12.075, and 3.158 groups of consumption records were generated in the process. The operational interface of the REPAST software is shown in Fig. 5, where the vertical axis indicates the absolute deviation between the sales pitch of the salesperson and the total number of consumers' purchases, and the horizontal axis indicates the number of groups of consumers who conducted transactions.

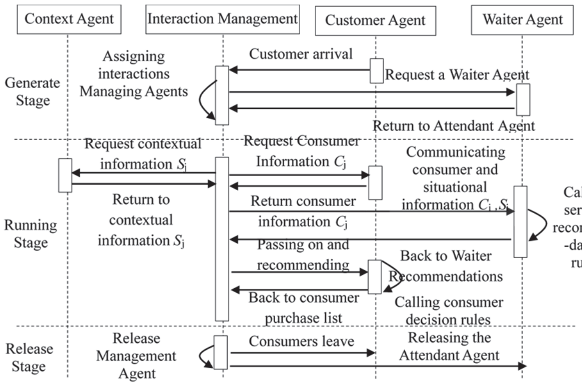


Figure 4 Interaction flow chart

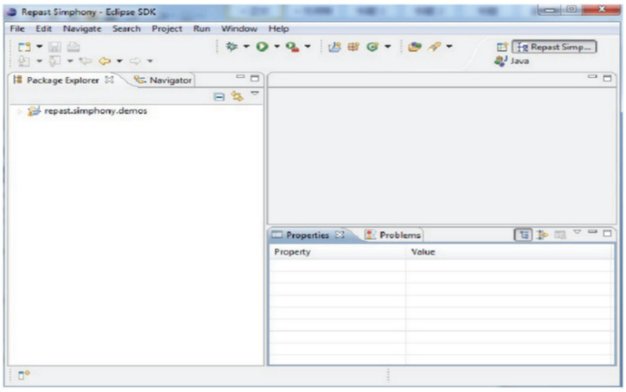


Figure 5 REPAST run chart

To further reveal the influence of consumers' personalized characteristics and the external contextual influences on the salesperson's personalized service pitch and consumers' final consumption behavior, two scenarios are adopted to conduct separate simulations and to evaluate and compare the effectiveness of both: one is a simulation experiment considering only the personalized characteristics of consumers, and the other is to consider the influence of external contextual factors.

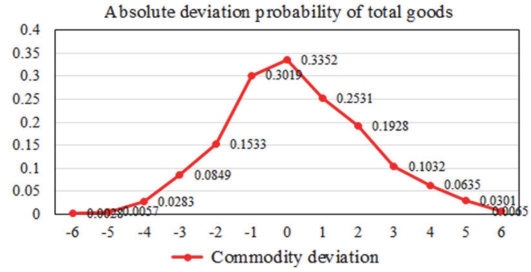
4.2 Analysis of Consumer Behaviour Without Contextual Factors

In the simulation experiments, only the influence of consumers' personalized characteristics is considered, i.e., changes in situational factors are ignored, and their influence parameter is set to 1. The specific experimental procedure is as follows.

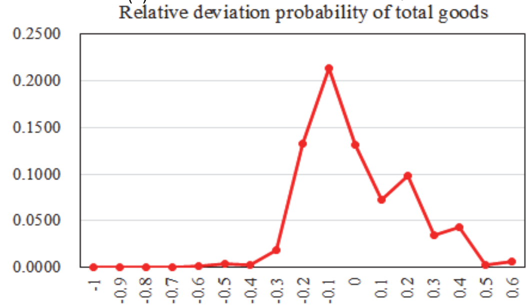
In the case of a sales pitch tailored to the consumer's personality, there must be some deviation between the list of products that the consumer wants to buy M and the list of products recommended by the salesperson S, which is particularly evident in the indicator of total purchases. Fig. 6a shows the probability distribution of the absolute deviation of W_a. The formulae for W_a and W_b are shown in Eq. (12), and Fig. 6b reflects the probability distribution of W_b.

$$\begin{cases} W_a = N_r - N_m \\ W_b = (N_r - N_m) / N_r \end{cases} \tag{12}$$

where N_r represents the total number of items sold by the salesperson and N_m represents the total number of items ultimately purchased by the consumer.



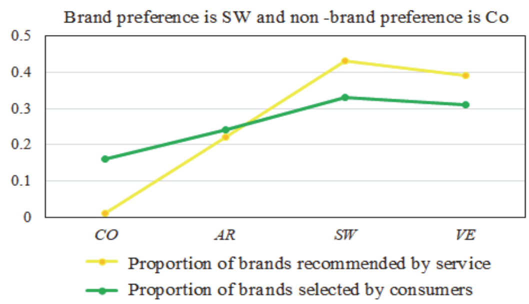
(a) Absolute amount of deviation W_a



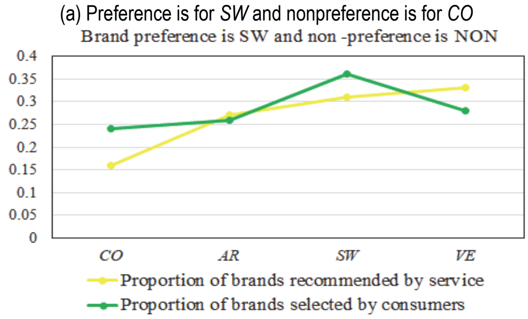
(b) Relative amount of deviation W_b

Figure 6 Probability distribution of absolute and relative deviations

Consumer behavior was further analyzed for a specific product category (e.g., luxury brand handbags), which was divided into four brands: COACH (abbreviated as *CO*), ARMANI (abbreviated as *AR*), SWAROVSKI (abbreviated as *SW*) and VERSACE (abbreviated as *VE*). Fig. 7 shows the percentage of consumers with a brand preference of *SW* and a brand nonpreference of *CO* and *NON*, respectively, compared to the percentage of consumers choosing each brand and recommending it (*NON* indicates that the consumer's brand preference/nonpreference is not known).



(a) Preference is for *SW* and nonpreference is for *CO*

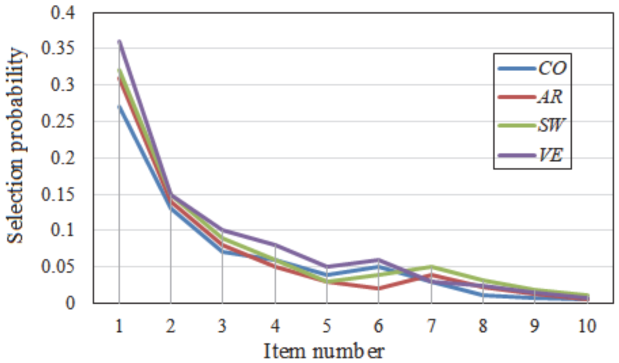


(b) Preference is for SW and nonpreference is for NON

Figure 7 Proportion of recommendations and choices by brand for different consumer preferences

It can be seen that the accuracy of marketing nonpreference brands is low and the accuracy of marketing preference brands is significantly higher than the former. Thus, marketing accuracy shows a positive correlation with the degree of consumer preference.

It can be seen that salespeople promoting different products from the same brand can also have a significant impact on the macro emergent results of consumers' final consumption behavior. However, due to the difference between the smaller number of items selected by consumers in the consumption process and the number promoted by the salesperson, as well as the variability in acceptance rates between individual consumers, the consumer selection rate is nearly the same for products numbered 3-7. Fig. 8b reflects the emergent results for all consumers in regard to product selection, represented by the frequency of selection of the 10 most popular products selected out of 120.



(a) 10 items from each of the 4 brands

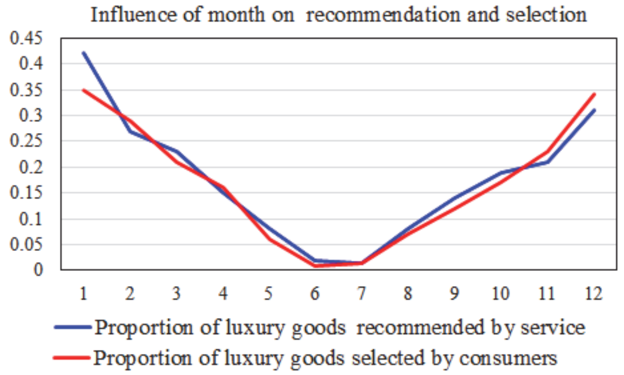
(b) Top10 selling items

Figure 8 Emerging results of consumer choice for specific goods

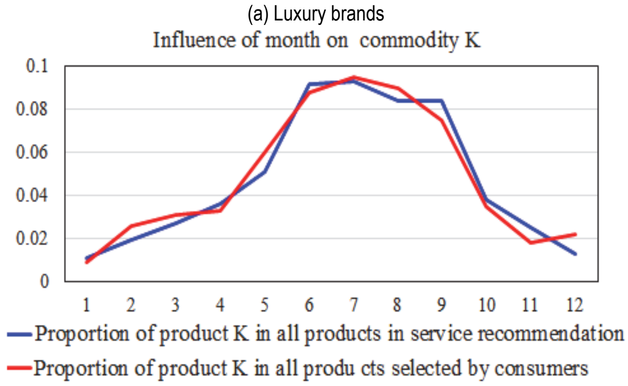
4.3 Analysis of the Influence of Situational Factors on Consumer Behavior

Depending on the real-time context, this experimental solution sets the contextual attribute participation values and adds situational factors to the agent to influence and change its specific behavior. The contextual factors added include month, scenario and holiday, and the simulation experiments with different contextual models added are analyzed below.

First, the analysis based on the month context model suggests that consumer behavior is influenced by the month context mainly in terms of the choice of seasonal and nonseasonal goods. Fig. 9a is a reference case of a luxury mink coat, which is highly seasonal, giving the proportion of recommendations and choices of the luxury mink coat over the twelve months of the year. Product K has obvious seasonal characteristics, and the effect of the monthly context on its choice is shown in Fig. 9b. Based on the results of the probability of being recommended and chosen in each month, it can be seen that in the three months of January, February and December, the product is less likely to be recommended and chosen, while in the four months of June to September, it is more likely to be chosen.



(a) Luxury brands



(b) Typical commodity K

Figure 9 Effect of situational factors by month

Second, the analysis based on the place context model suggests that consumers' preference and liking of brands is a reflection of their consumption behavior being influenced by place status. Fig. 10 shows the proportion of consumers choosing the four luxury brand jewelry items and the overall average brand (AVERAGE) when based on different place states.

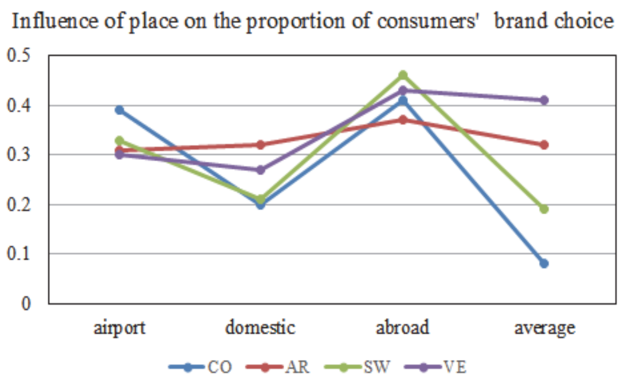


Figure 10 Influence of situational factors

As seen in Fig. 10, the largest proportion of consumers choose the *VE* brand in the average scenario state, followed by the *AR* brand; when consumers return to their home city, the proportion of consumers choosing the luxury brand also decreases, while the proportion of consumers choosing the general brand increases; in the process, the largest proportion of consumers choose the *VE* brand, followed by the *AR* and *SW* brands, and as the proportion of consumers choosing the *CO* brand itself is not very high, the change is relatively moderate, as it is not so highly selected.

Finally, a holiday contextual factor was added to the analysis, in which the difference in per capita purchase of the product was used to reflect the impact of this contextual factor on consumer purchasing behavior. The difference in service recommendations and per capita purchases of goods by consumers during different holidays is shown in Fig. 11. As seen in Fig. 11, consumer spending levels will be significantly higher during the holiday season. The number of goods purchased by consumers on typical holidays will increase by approximately 35% and 56% compared to the number of goods purchased on regular holidays and nonholidays.

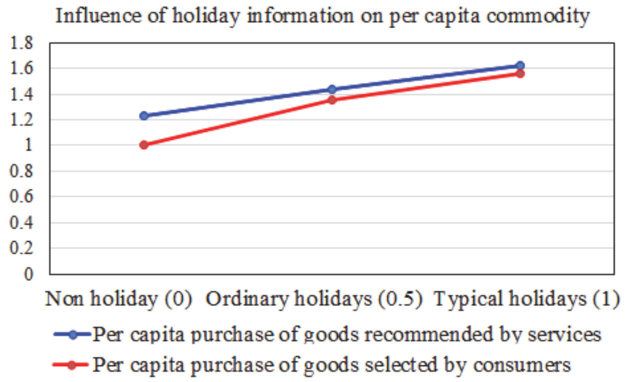


Figure 11 Influence of situational factors for holidays

4.4 Analysis and Comparison of the Effectiveness of the Two Options

Mobasher et al. [22] provide a comprehensive evaluation metric measure for recommender systems to assess the validity of simulation results from simulation models, where the metrics include coverage (*coverage*), accuracy (*precision*), and composite measure (*F*). These metric terms are used to measure the breadth of recommendations, accuracy and the combined results of the two, and the method is calculated as follows.

$$\begin{cases} coverage = |M \cap S| / |M| \\ precision = |M \cap S| / |S| \\ F = 2 \times coverage \times precision / (coverage + precision) \end{cases} \tag{13}$$

In Eq. (13), S represents the set of recommended products; M represents the set of products that the consumer ultimately decides to purchase.

The results obtained from the assessment of the effectiveness of the recommendations by consumer type and without adding any situational factors are shown in Tab. 1. The results in Tab. 1 show that the coverage, accuracy and effectiveness of the model for all types of consumer recommendations ranged from 32% - 65%, 63% - 87% and 84% - 93% respectively. For example, the lowest recommendation effectiveness was 84.02% C_4 for and the highest was 90.15% for C_5. The main reason for this phenomenon is that the probability of different types of consumers appearing during the implementation of the simulation experiment also varied, resulting in a large difference in the data collection for different types of consumers. This is because there were also differences in the probability of different types of consumers appearing during the implementation of the simulation experiment, resulting in large quantitative differences in the data collection for different types of consumers, thus affecting the validity of the recommendations.

The results are shown in Tab. 2, which classifies the situations according to the type of holiday, adds each type of situation factor to the model and evaluates the validity of the model. Based on the results, it is clear that the effectiveness of the recommendations made by salespeople to consumers during general holidays and typical holidays is 83.7% and 87.24%, respectively. Tab. 2 also shows that consumers are more likely to accept recommendations during typical holidays. However, in the implementation of the model, the consumer behavior of consumers in this context needs to continue to be refined as the conditions set for general holidays are broader, and the rules for service recommendations when adding contextual factors should continue to be improved.

Table 1 Assessment of the validity of recommendations without contextual factors

Type of consumer	*Coverage*	*Precision*	*F*
C_1	0.3529	0.6702	0.8527
C_2	0.4298	0.7824	0.8433
C_3	0.5670	0.8113	0.8789
C_4	0.3214	0.8650	0.8402
C_5	0.5706	0.6321	0.9015
C_6	0.6528	0.6942	0.8740
All consumers	0.4892	0.7130	0.8623

Table 2 Assessment of the validity of recommendations considering holiday scenarios

Holiday Type	*Coverage*	*Precision*	*F*
Nonholiday	0.6239	0.5802	0.6311
General holidays	0.7184	0.7625	0.8370
Typical holidays	0.8056	0.8890	0.8724
All consumers	0.6830	0.7126	0.7803

Finally, the validity of the personalized recommendation simulation models of the two scenarios without and with the addition of the holiday scenario factor was evaluated, and the results are shown in Tab. 3. Comparing the measurement results of the three indicators shows that the measurement results of each indicator were improved by more than 20% when the contextual influence was taken into account compared to without the addition of the contextual factor, indicating that the addition of the contextual factor can significantly improve the model validity. The results are comparable to those of the recommended studies, which have the highest validity of the other programs.

Table 3 Comparison of the effectiveness of the two options

Programme	*Coverage*	*Precision*	*F*
No scenario	0.4836	0.5519	0.6028
There are scenarios	0.6155	0.7882	0.8710
Range of optimisation	24.27%	25.03%	22.54%

5 CONCLUDING REMARKS

This paper investigates the intrinsic relationship between personalized recommendations for heterogeneous consumers of duty-free shops and their consumption behavior and evaluates their effectiveness based on an agent simulation model. This approach has the dual advantage of being able to simulate and capture the 'emergent nature' of the system.

At the same time, this paper establishes an agent simulation model to study the consumption behavior and purchase preferences of heterogeneous consumers in duty-free shops by adding contextual factors. Two submodels of subheterogeneous consumers and contexts are constructed, consumer choice rules and service recommendation rules are set, it is determined whether or not context is considered as a variable to establish the two models, and empirical simulation experiments are conducted. The empirical simulation results show that there is a certain correlation between the consumption behavior of heterogeneous consumers of duty-free shops and personalized recommendations, and their effectiveness can be measured by the emergence of the system in the process of individual interaction. Moreover, the agent model is used to analyze the choices of heterogeneous consumers in duty-free shops and the possible recommendations of salespeople, which shows that the consumption of heterogeneous consumers in duty-free shops as a whole is related to different contexts and to salespeople's recommendation strategies. Therefore, duty-free shops should vigorously develop membership systems, use their members' personal information and consumption information to determine their purchasing preferences and buying behavior, and formulate different sales promotion strategies for different consumers to achieve effective prediction and mastery of heterogeneous consumers' consumption behavior.

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Contact information:

Yue LIN, Doctor
School of Economics and Management,
Beijing Jiaotong University,
No. 3 Shangyuancun, Haidian District, Beijing 100044, China
E-mail: 18113058@bjtu.edu.cn

Dan CHANG, Professor
(Corresponding author)
School of Economics and Management,
Beijing Jiaotong University,
No. 3 Shangyuancun, Haidian District, Beijing 100044, China
E-mail: denisechang@yeah.net