An Agent-Based Modeling Approach for Understanding Drivers of Consumer Decisions on Foreign vs Domestic Products: Case study of a local refrigerator market

Abstract

Despite extensive studies on consumer behavior and decision-making, the social influence of consumers on each other has not been widely investigated. To incorporates such interactions, in this study we propose and apply an agent-based simulation model where consumers are defined as agents. The purchase behavior of each agent is characterized as a function based on the concept of the black-box model for consumer behavior.

In particular, we investigate the effect of consumers' social network and its interaction with the marketing mix parameters (4Ps). A case study of household appliances in a local market is used to demonstrate how the dynamics of preferences between domestic and foreign brands occurs. The simulation model is used to examine the effect of eight scenarios related to these interactions. The obtained results are compared and the most important factors are determined as product features and price.

Keywords: Agent-Based-modeling, Consumer behavior, Black Box model, Perception on foreign vs domestic products, Social influence, Consumer purchasing decisions

1 Introduction

Foreign brands are commonly perceived as superior or better quality by customers in developing countries. The perception makes foreign brands favorable for customers while influencing the customer preferences to the foreign branded products over domestic brands' products (Rossanty and Putra Nasution 2018; Steenkamp 2019). Although some domestic products are better or at least at the same quality as their foreign counterparts, customers keep purchasing the products of foreign brands due to the positive views or feeling of trust towards these products with foreign brands (Thuy Hang Dao and von der Heidt 2018).

However, ignoring the local aspects for brands can cause market share loss (Heinberg 2017). For instance, a simple and strong attitude (e.g., buy this product, this is American) may lead to a negative consumer reaction in some markets (Bahaee and Pisani 2009; Hoang et al. 2022). In fact, global brands are unable to attract the entire market due to cultural differences among countries (Grigorescu and Zaif 2017; Sarkar et al. 2021), or economy and consumer perception compared to their local rival brands (Kozlenkova et al. 2021; Steenkamp 2017). Therefore, local brands that meet local needs are recognized as the main rivals of their global counterparts (Samiee 2019). In competitive markets where customers have a significant number of choices, resource allocation strategies should be directed to address three fundamental questions: *(i)* Who are the customers? *(ii)* What are their needs and desires? and *(iii)* what do they think about commodities and marketing activities? (Gielens et al. 2021).

Research in consumer purchase decision-making and consumer interactions may help understand about market dynamics. Traditional studies about consumer decisions are mainly limited to data mining, static equilibrium-based mathematical and statistical techniques for modeling consumers' socio-demographic and behavioral data (Huiru et al. 2018). In particular, we can refer to several methods such as consumer ethnocentrism tendencies scale (CETSCALE) (Haghighi and Hosseinzadeh 2009); gap analysis (Heydarzadeh and Kheyri 2009); Statistical methods and econometric models (Hussain et al. 2007; Pawlowski et al. 2009).

Nevertheless, these methodologies are oversimplified lacking peer-to-peer interaction and feedback features and are incapable of interpreting individual behaviors. These models generally provide a static image of consumer behavior while it is dynamic and variable over time. System dynamics and agent-based modeling (ABM) are more capable and appropriate methods for modeling such complex issues. Although few studies like Zhao and Zhong (2015) have used system dynamics to investigate the consumer behavior, multiplicity of variables and the interactions between them still challenge the modeler in using this method. Moreover, consumers' preference studies in the fields of psychology, economics, sociology and marketing include constituents complex social systems (see Kuhn Jr et al. 2010; Crooks and Heppenstall 2012; Santos et al. 2014; Huang et al. 2021; Jager 2021). Despite ABM approach is a strong alternative for consumer behavior modeling as proven by studies of Ben Said et al. (2001), Zhang and Zhang (2007) and Schramm et al. (2010), its applications has remained limited in the existing consumer behavior literature.

Consumer choices in a social system reflect preference decisions made by individual consumers within a complex system, which are resulting from: *(a)* interactions among individuals' personality, *(b)* perceived characteristics of goods and *(c)* social influence (Melero and Montaner 2016; Testa et al. 2018; Stavrakas et al. 2019). To capture the interaction of market members within such a complex and adaptive system the ABM methodology is applied for simulating the system. It is capable of incorporating the system and its members' interactions with extension of economic approaches. This complex system adaptation can reveal important results that may provide further innovations in marketing. The ABM provides a great opportunity to analyze, examine and explain institutional and social norms, and to evaluate the emerging collective behaviors in particular contexts. "ABM is a relatively new methodology and marketing researchers have been among the early wave of scientists who have used this methodology" (Nejad 2016, p.14).

This study aims to model customers' purchasing preferences in domestic or foreign goods using the agent-based modeling. Analysis of the reasons for the preference of foreign products may help policy-makers to better understand the consumer behavior and establish appropriate policies to direct consumers' attention towards domestic products for national economical benefits. In our agent-based preferences model the product and consumers' characteristics are incorporated in their corresponding agents. Then, the simulation model is created and implemented, and the corresponding results are obtained.

The rest of this article is structured as follows. In the following section, the relevant literature regarding consumer choice and agent-based models is reviewed. In Section 3, we describe our agent-based model and the relevant factors such as cultural, social, economics, personal and marketing aspects. Then in Section 4, the results of our simulations are presented and finally, Section 5 discusses the results of the simulation model, concludes the article and provides suggestions for future research.

2 Literature review

We review the relevant studies in consumer decision, ABM simulation and their intersection in the following subsections.

2.1 Consumer behavior in decision making

Consumer behavior "attempts to understand both individually and in groups about buyer decision-making processes" (Zhao et al. 2021, p.101591). It is suggested that the best way of understanding consumers' behavior is investigating about their decision-making process first (Dulam et al. 2021). Decision making process compromises various dynamics such as effort, money, time, disposal or consumption of products and therefore it is highly influenced by external and internal factors. These factors are broadly associated with emotional, mental and behavioral states of consumers. However, it is also known that role of family, price, promotion, motivation, lifestyle, brand, and type of product is significant in this decision making process (Mishra et al. 2021; Lawson et al. 2021).

Several models have been developed to understand consumer behavior in decision making. For instance, the purchase behavior model of Engel et al. (2005) serves as a plan for organizing the knowledge structure of consumer behavior. Dennis et al. (2009) derive a model based on the rational behavior by adding several other factors. They present a model to study consumer's electronic behaviors. According to Orji (2013), most of the consumer behaviors can be explained by the classic model of Alport (1954) - Socio-PsychoAnalytic model- which states that "a feeling favorable or unfavorable, towards a person or thing, prior to, or not based on actual experience". He has identified several major internal and external affecting factors.

Many well-recognized psychological theories and their combinations such as motivational processes, social comparison theory, theory of reasoned action, human needs and social learning theory are underpinned as the theoretical base for consumer behavior in Ali et al. (2006). Recently, Bettiga and Lamberti (2020) emphasize the significance of emotions such as happiness in the decision making process of consumers.

In another viewpoint, Kim et al. (2008) develop a theoretical framework to describe the processes of trust-based decision-making for consumer use in the case of purchasing a site. Ben Said et al. (2001) propose a model used in project called CUBES (Customers BEhavior Simulator) aiming to develop software that simulates consumer behaviors when a market is competitive with existing various brands. Their model guides how to build a large pool of consumers virtually and individuals for reproduction of real market properties (segmentation, evolution) as independent from a given product.

Besides the well-known marketing stimuli, social influence reduces decision anxiety and simplifies the information search process that affects the preferences and decisions of consumers. The impact of such subjective norms (i.e., friends' experiences) eases the decision-making process. Kotler and Armstrong (2017) suggest a stimulus-reaction model for consumer behavior, which consists of four parts: marketing stimuli, environmental incentives, buyer black-box and buyer responses. The black-box itself consists of two parts: *(i)* buyers' individual characteristics that affect their perception and reaction to the stimulus; *(ii)* buyers' decision-making process that affects their behavior. Their model is widely used as a basis for consumer behavior according to its comprehensiveness and usefulness compared to other models. Fig. 1 depicts this framework known as the black-box model. The social factors in this model encompass small

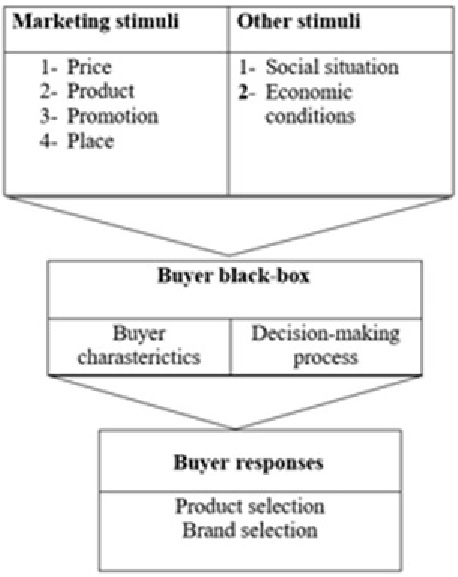


Figure 1: Black-box model (Kotler and Armstrong 2017)

groups, family members, and the social status and consumer social role, and they strongly affect consumer responses (White et al. 2019; Hermawan 2021). Each individual is in connection with other people and therefore he or she is under influence of other groups. The social influence supports potential buyers and persuades them about having consumption decisions (Amblee and Bui 2011). Furthermore, these reference groups directly or indirectly play a role (by being a point of comparison or reference) in forming the behavior or attitude of the individuals.

The above-mentioned studies describe the components of individual behavior. There has been a tendency in marketing studies to reduce the complexity of previous models in order to obtain an operational decision making tool for in marketing. These models offer a general outline of consumer behavior but fail to specify cognitive processes for operational descriptions. As a result, they are not well-suited for modeling practical behavior of consumers in a large scale

(Mishra et al. 2021). In addition, these outdated models do not describe the social dynamics expressed by various types of interactions in the real market. If these goals are achieved, a better understanding of the consumer behavior and therefore more precision in examining them will be obtained.

2.2 Agent-Based Simulation

The traditional models of consumer preferences in the literature have limitations despite providing a strong theoretical basis. These well-known models are limited to reflect real world dynamics, since effective factors of the social system (i.e., market segment and brands) and their interactions with each other in decision process are lacking. It is difficult to have predictions in some cases (e.g., when the population of consumer differs, or social influence is a determining factor in decision process) (Jager 2007).

Additionally, econometric models are not capable of incorporating the differences in characteristics of marketing mix and brands clearly as they are not in the individual level but in aggregate level instead. ABM introduces a huge potential to those models in literature for addressing their limitations although econometric and explanatory models are not replaced with the ABM because they have different outputs (Garcia 2005; Wang et al. 2009). Facilities of ABM are beyond the traditional modeling approaches such as identifying the market complexities and intricacy of a market at micro level.

An agent is a highly abstract conceptwhere the common belief about agents in artificial intelligence is that there should be some attributes to consider any entity as an intelligent agent: 1) autonomous behavior, 2) individual worldview, 3) communicative and cooperative capacity, 4) intelligent behavior; and 5) spatial mobility (d'Inverno et al. 2004). Hence, ABM is called as a bottom-up technique which deals with complexities in a complex system environment since offering a robust tool (Grimm et al. 2005; Axelrod 1997; Richardson 2004; Zhang and Zhang 2007). Applications of agents with those characteristics are widely visible in engineering, computer science, economics, and sociology.

The ABM can be also called as Multi-Agent System because it consists of more than one agent. Jennings et al. (1998) rank the four characteristics of Multi-Agent Systems as: *(i)* each agent is limited to bring a solution with a given problem as it does not have information or capabilities sufficiently; *(ii)* there is no global system control; *(ii)* data is decentralized; and *(iv)* computation is asynchronous. In such a system, the interaction between the individuals creates the overall behavior. In other words, the macro-level behavior in the entire system is the result of those micro-level behaviors of individual agents (Schillo et al. 2000).

An ABM is structured by four main components: agent, environment, time and interaction between agents. The general process of an ABM represented as follows:

- Design of conceptual model
- Choosing the programming base

- Designing agent decision-making module
- Defining spatial and temporal interactions of agent
- Entering real-world data
- Running the model several times
- Analyzing spatial and non-spatial data output
- Comparing the model outputs with real data.

In addition, ABM helps with identifications of emergent behaviors and interactions in the stimulated market (see Fig. 2).

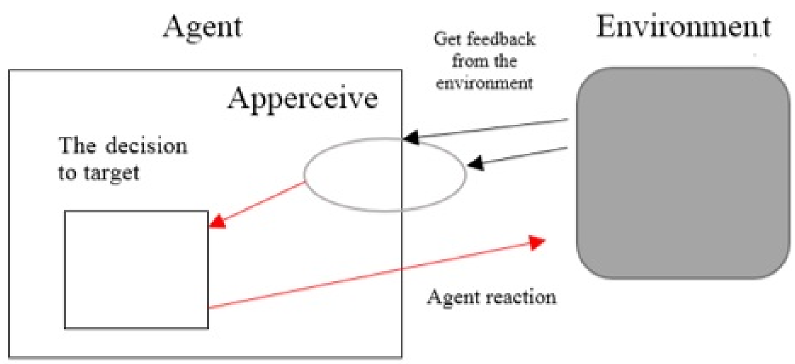


Figure 2: A schematic depiction of agent and environment interaction

2.3 Agent-Based Modelings in Consumer behavior

Although the studies investigating consumer behavior via simulation modeling, and in particular ABM, started a couple of decades ago, the literature in marketing science is not dense with application of this tool. In this section, we briefly review the existing relevant articles in the context of our study and provide a summary categorization of them based on the applied theory, investigated input and output, features of the simulation model and applied cases.

In one of the pioneer studies Ben Said et al. (2001) aim to identify the effective marketing strategies in the competitive markets through the creation of a virtual consumer population that can be simulated. The cognitive features and main concepts pointed out by studies about consumption in the field of marketing and psycho-sociology can be easily interpreted. Their study particularly shows the use of genetic algorithms (GA) and multi-agent systems together for the purpose of fitting the virtual consumers population characteristics with a global realistic behavior.

Zhang and Zhang (2007) apply an ABM in consumer purchase decision-making for exhibition of the decoy effect phenomenon by creating a high number of heterogeneous consumer agents in an artificial market. Their multi-agent use of ABM in analyzing consumer behavior and markets enables the modeler to deal with the dynamic changes and complexities in the real-world business environment. Schenk et al. (2007) present a particular agent-based micro model focused on individual and store data gathered about grocery shopping in northern Sweden. The gathered large size of data for their study increased the reliability and validity for obtaining the simulation results. By a different approach and product market, Chen et al. (2008) use Buyer Collective Purchasing (BCP) model in a multi-agent framework. Their prototype system gives information about how suitable their model is by analyzing the data on a laptop purchasing pattern. In another study from a different sector Ulbinaite and Le Moullec (2010) propose an ABM framework for investigating consumer behavior in the insurance industry. In their model customers considered as agents have interaction with other insurance customer agents through local and global social networks.

Roozmand et al. (2011) employ an ABM for simulating consumer behavior according to a utility function which is defined over power distance dimension of national culture, extroversion, model of personality, and social status and social responsibility needs. They validate their model based on wealth and car purchasing data in some European countries. Similarly in using utility function, Baptista et al. (2014) propose an ABM of consumer behavior relying on the beliefs, desires and intentions (BDI) architecture and the neoclassical theory of utility maximization. Their model is able to simulate a dynamic environment of heterogeneous deliberative consumers.

Schramm et al. (2010) touch upon an AMB with consumer and brand agents. ABM enables them to model diffusion at the brand rather than product-category level and the resulted diffusion curve of brand and product, which allows diffusion study in both micro and micro level. Also Karakaya et al. (2011) inspects marketing strategies in the effect of Word-of-Mouth (WOM) via an ABM, while Jiang et al. (2016) examine the role of knowledge in the diffusion of competitive brands in online platforms and therefore, e-WOM is subsumed in their model together with creativeness, brand image and perceived utility. Furaiji and Łatuszyńska (2017) is another study which investigates the marketing strategies with the ABM approach. They have simulated consumers purchasing behavior in a local electric appliance market.

Among the recent publications, Zhang and Zheng (2019) develop an ABM based on a utility function which consists of three factors, quality, price and promotion to study consumer behavior, while Du and Xiao (2019) examine pricing strategies via simulation considering consumers and retailers as agents in their model. Rand and Stummer (2021) discuss the strengths and criticisms of ABM in market diffusion of new products and Zhang et al. (2021) address a contemporary experience by studying user-generated contents in international tourism. They employ ABM to identify potential causal mechanisms of individual tourists behavior in destination choices. In another modern topic, Jiang et al. (2020) propose an ABM to explain the effects of clicking position and the number of items on a review web page on the user posting behavior. Finally, Stummer et al. (2021) combine ABM with scenario analysis to inspect effect of strategic technological decisions in future.

The attributes of the above-mentioned studies are presented in Table 1. As shown in this table, on average only one study every other year has been published since 2001 and therefore, there is still room for further research in application of ABM that can afford new insights for marketing managers. In the last row of the table we have provided ours to give a clearer dimensions of our contributions. In addition to particularity of our case study and primary data collection, a rigorous statistical validation and verification of our data and model is carried out through this study and the results are given in Section 3.

Table 1: Summary of the consumer behavior studies with the application of ABM

Paper	Theory / Assumption	Inspected stimuli (input variables)	Inspected response (output variables)	ABM basis	Real case study	Software
Ben Said et al. (2001)	Behavioral primitives	5 behavioral attitudes	Market share of 3 products	Homogeneous consumer	NO	CUBES
Zhang and Zhang (2007)	Decoy effect	Psychological personality (motivation function)	High vs. Low brands	Heterogeneous consumer agents	NO	Netlogo
Schenk et al. (2007)	Spatial Decision Making	Store attributes (Price, service,atmosphere, etc.)	Competition among stores (supply side)	Heterogeneous consumer agents	YES: grocery: Sweden	SeSAm
Chen et al. (2008)	Buyer Collective Purchasing	Buyer preferences (negotiation, bargaining)	Transaction costs, convenience of tools and environment	Online buyer group and agents	NO	Netlogo
Schramm et al. (2010)	Consumer diffusion paradigm	Brand attributes (i.e., features, price, and promotion)	The brand and product diffusion curve	Consumer and brand agent	NO (s.d.)	Netlogo
Ulbinaite and Le Moullec (2010)	Insurance industry	socio-demographic features (general experience, education,purchasing power, etc.)	Purchase decision under local family, social networks & global networks	Heterogeneous consumer agents	NO	Netlogo
Roozmand et al. (2011)	Power distance of national culture	Utility function based on (Extroversion, Agreeableness and Openness five-factor personality model)	A defined status measure of agent	heterogeneous consumer agents	NO (s.d.)	Repast Symphony
Karakaya et al. (2011)	Marketing strategies & WOM	price, promotion, quality levels of products and WOM effect.	Purchasing decision of consumers	Heterogeneous consumer	NO	-
Baptista et al. (2014)	Beliefs, Desires and Intentions architecture and utility maximization	Price, income, substitution and complementary effects.	BDI of customers vs. dynamics of market	Heterogeneous consumer agents	NO	Coded in C#
Jiang et al. (2016)	Brands diffusion, pricing mechanism	Competition factors (creativeness, brand image, self-perceived utility and eWOM)	Brands market share in online competition	Heterogeneous consumer agents	NO (s.d.)	Netlogo
Furaiji and Łatuszyńska (2017)	Collective interaction between agents and the environment	5 exemplary marketing strategies (advertising promotion, discounting promotion, etc.)	Buying choice of consumers	Consumer and vendor	YES: electric goods: Iraq	AnyLogic
Du and Xiao (2019)	Two suppliers in Supply chain	Pricing strategies of two supplier	Profit of the retailer	Homogeneous retailers	NO	coded in Java
Zhang and Zheng (2019)	Utility theory	Quality, price and promotion	Purchase over two commodities	Homogeneous consumer	NO	Netlogo
Jiang et al. (2020)	Online review systems (ORSs)	Clicking position on webpage	Posting behavior (reviews & responses)	Homogeneous user agents	YES: Webpage posts	Netlogo
Stummer et al. (2021)	Scenario Analysis, smart products	Market characteristics & consumers data	Future market behavior	Product and consumer agents	YES: consultancy	AnyLogic
Zhang et al. (2021)	User-Generated Contents(UGC) Tourism Distribution	Three UGC behavioral features, Innovation diffusion theory	Number of international arrivals to destinations	Learning tourists & heterogeneous destination	NO (s.d.)	Netlogo
Our study	Marketing mix & Social influence (black box)	Marketing 4Ps and sensitivity of consumer to them	Domestic vs. Foreign brands	Heterogeneous consumer agents (social classes)	YES: fridge: Iran	Netlogo

s.d.: secondary data

3 ABM methodology for consumers' preference

A guideline to rigorously practice of ABM in marketing research in terms of widely accepted standards have been provided by Rand and Rust (2011). In the following subsections we present the details of our data sampling as well as some statistics for validation and verification purpose to adhere to the rigorousness framework.

3.1 Building blocks and overview of the simulation model

To model the dynamics of the real world and closely reproduce the realized data, first we need to define different agents which can interact in a configured setting imitating the real social network. In the modeling software, agents can be translated to public classes having a member function which encapsulates their properties. Such a function in our model is called *preference function*, denoted by PRE, which determines a compound value corresponding to the interaction between the expectations of the consumer agents, and the characteristics of the product brand as well as the social interactions that consumer adopted. In fact, as each agent performs under several behaviors it makes a preference decision according to the PRE function.

The configuration of the network by which individuals are connected, is another input of the model. Among the well-known network structures representing the social connections, both of the following might be suitable: *(i)* the random network of Erdős and Rényi (1960) and *(ii)* the preferential attachment network configuration of Barabási and Albert (1999). In the former (ER), the percentage of all agents which connected to other agents, so called *network density*, is the key parameter to control; whereas in the latter one (BA), some consumer agents have a significant number of neighbors in the network compared to other consumers who have a limited number of neighbors. However, we have only employed BA network as one may argue that ER is random and not suitable for social networks in this context because they are not random in reality. Thus, BA configuration is more realistic in representing social networks (Barabási and Albert 1999). The BA network is a structure in which new agents (consumers) expand a network by connecting to some older agents that are the most connected. We can scrutinize consumers' behavior by adhering to the above-mentioned connections and influences.

Other main inputs of the model are: consumer parameters, product parameters and environment parameters, associated with factors affecting the customer preference of products, known as marketing mix (4P's): Product feature, Price, Promotion and Place. Additionally, the customer sensitivity to each of these variables are also considered as inputs to the model (PRE function) for further analytical purposes.

The general overview of the simulation steps is depicted in Figure 3 and parameter setting is discussed in the next subsection.

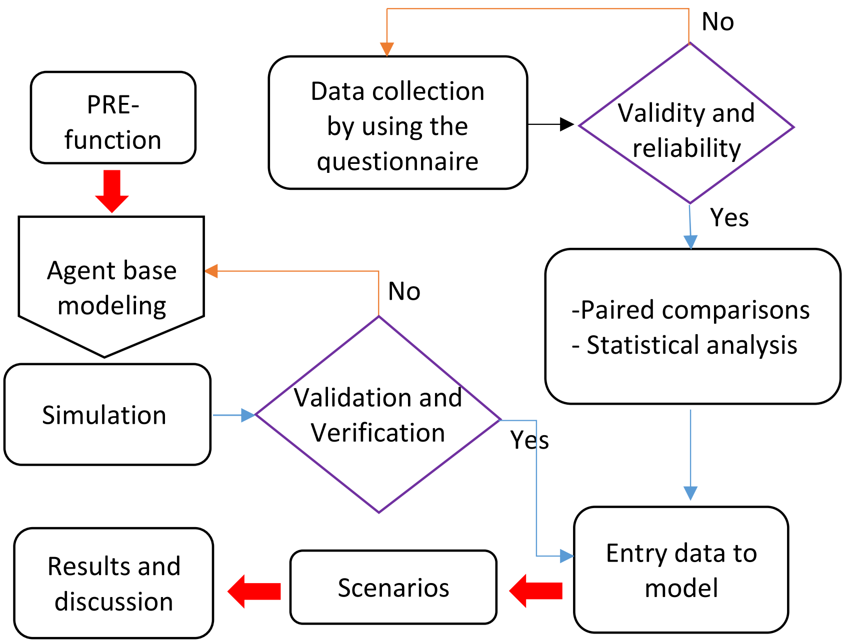


Figure 3: Simulation and data collection process in the research

3.2 Data collection and parameter setting

To estimate the aforementioned characteristics, a survey was conducted on white goods market in Tabriz, a highly populated city in northwestern Iran during July 2018. The population of interest which was sampled is limited to refrigerator buyers within that month. These people were identified through the introduction of home appliance stores. It is impossible to observe a fully randomized sampling as the entire population is unknown.

A questionnaire including 19 consumer-related questions as well as demographic data such as gender, age, occupation, education, approximate income and area of residency was designed to obtain the parameters associated with the consumer agents and their social class, respectively (see Appendix A1). It was designed based on the operational characteristics of components and its validity was confirmed through content validation by corrective comments of eight faculty members with specialty of business management. Through the data collection from 110 accessible buyers, the majority of them returned the questionnaire and we ended with the sample of size 101. The demographic profile of participants is listed in Table 2.

Table 2: Demographic profile of the participants in the survey

Gender	Age	Occupation	Education	Income range \$	Area of residency
57M 44F	under 30: 29 [30,50):47 [50,70):21 above 70: 4	unemployed: 7 self-employed: 36 employee: 36 employer: 10	High school: 32 BSc: 42 MSc: 19 PhD: 8	[0,1000): 59 (1000, 5000]: 25 [10000,∞):18	Poor: 24 Average: 61 Rich: 17

The reliability of the questionnaire was evaluated using Cronbach's alpha as given in Table 3.

The sensitivity of consumers to each of the attributes was measured by their pairwise com-

Table 3: Reliability of input parameters gathered via questionnaires

Variable	Cronbach's alpha
Product feature	0.718
Promotion	0.751
Place	0.726

parisons within each questionnaire. However, the population is not heterogeneous in terms of such a sensitivity. To address this issue, assuming that the society is normally distributed, we have used a normal distribution function. Thus, a random number in the interval of $[\mu-\sigma, \mu+\sigma]$ was assigned to each consumer agent in the simulation environment corresponding to their social class, where μ is average sensitivity to attributes and σ is its standard deviation. Their values are given for different social classes in Table 4. As shown in the table, a t-test is also used for checking differences between sample data and the population and the results guarantee that the sample is generalizable.

Table 4: Parameter estimation for the sensitivity of different social classes to marketing mix

Social Class type (sample size)	Normal distribution parameters	Sensitive to price	Sensitive to feature	Sensitive to promotion	Sensitive to Social Influences
LOW(59)	μ	0.2195	0.4103	0.1136	0.2566
	σ	0.1315	0.01268	0.1144	0.1267
	t-test	0.000	0.000	0.000	0.000
Middle(25)	μ	0.1323	0.2987	0.172	0.397
	σ	0.0765	0.131	0.1247	0.1005
	t-test	0.000	0.000	0.000	0.000
High(17)	mean (μ)	0.1438	0.5359	0.0833	0.2319
	σ	0.0897	0.0665	0.0855	0.2319
	t-test	0.000	0.000	0.000	0.000

Finally, it is worthwhile mentioning that apart from the survey data the price of the product was obtained by averaging its selling prices in different regions of the city. The marketing mix parameters (4Ps) are estimated following Schramm et al. (2010) and summarized in Table 5.

Table 5: Estimated mean of the marketing mix parameters

Brand type	Price	Feature	Promotion	Place
Domestic	0.2367	0.5590	0.6270	0.6137
Foreign	0.7632	0.7462	0.6683	0.6711

3.3 Preference function

The preference function includes the items listed in the consumer behavior model and is derived from the relation used by Zhang and Zhang (2007). The external factors in preference models are the independent variables which are processed by agents according to their encapsulated personality properties. Agents make different choices based on achieved preference motivations. Following the general consumer behavior model of Solomon (2017), social class is considered as part of the culture: reference groups entered in the social influence are as sub-social factors; while sensitivities of every social class to the marketing mix are as personal characteristics and psychological factors of consumers. Each time a consumer agent interacts with a product agent, the model calculates the value of price, features, promotion, and social influence indices. These four indices are used to calculate the consumer's preference threshold (PRE). In fact, PRE defines a compound measure consisting of the interaction between the expectations of consumer agents and the characteristics of the product agents. The higher the value of PRE, the greater preference of the consumer agent is. Thus, PRE is calculated as:

$$PRE_i = PS_i \times P_i + FS_i \times F_i + sus_i \times ad_i + ft_i \times infl_i \tag{1}$$

where PRE_i is the preference measure of product (brand) i (i =D, F; D:domestic; F: foreign) for a consumer agent. These arguments and the threshold with which the PRE is compared, are defined in Table 6.

Table 6: List of parameters used in simulation model

Notation	Definition
PRE_i	Preferences function of product i
TR	Preference threshold
PS_i	Price sensitivity of consumer agents to product i
P_i	Price of product i
FS_i	Feature sensitivity of consumer agents to product i
F_i	Feature (quality) of product i
sus_i	Susceptibility of consumer agents to advertisements of brand i
ad_i	Advertisement intensity for product i
ft_i	Follower tendency of the consumer agent under the influence invoked by other agents about product i
$Infl_i$	Influence index observed by a consumer agent from other consumer agents for product i

The decision of a consumer agent to prefer a product hinges on the consumer's product expectations, product's characteristics and the interaction between them, which are all subsumed in the PRE function. The parameters corresponding to the consumer agents are set according to Table 4 for three social classes of consumers, whilst the relevant parameters of the commodity agents are set according to Table 5 for the foreign and domestic brands.

4 Simulation

After compiling a preference function, the simulation model was designed using NetLogo software. Fig 4 shows a view of the constructed model in the software interface.

4.1 Implementation

To simulate the market, initially a number of consumer agents with different characteristics was created based on demographic data. Thus, social members were classified into three classes

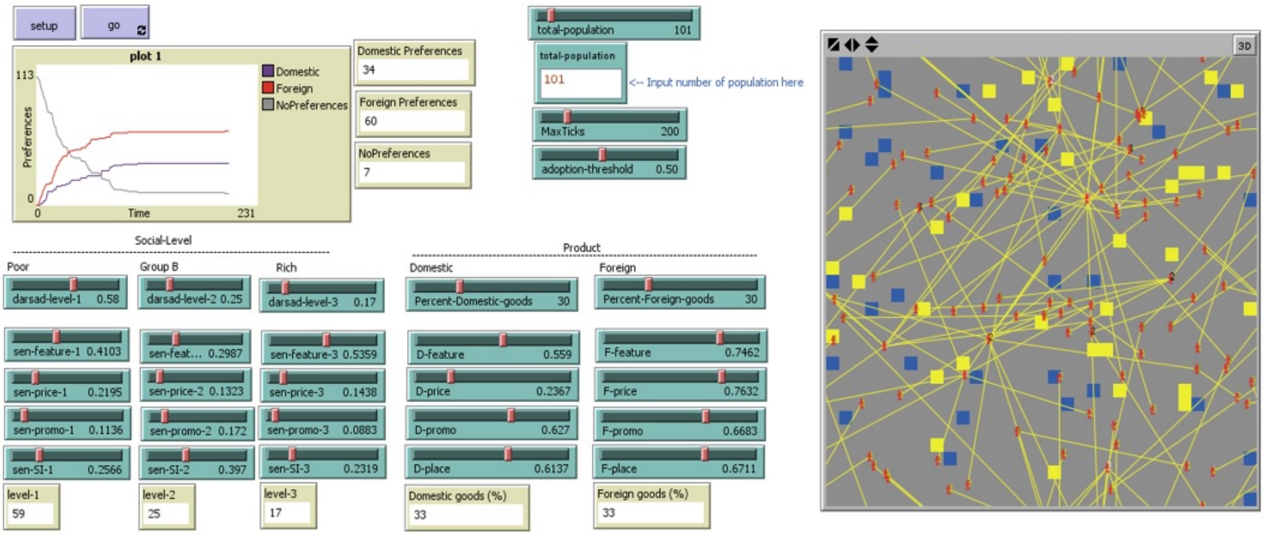


Figure 4: A view of the model on the NetLogo software

based on income (poor, middle and rich), while the ratio of each class can be changed by the user. Assuming that domestic or foreign brands are randomly distributed over the population, it is also set to be random in the simulation environment. Furthermore, it is assumed that the product properties are specified at the start of the simulation and it remains constant during the simulation period.

Each consumer agent is involved in two different kinds of interactions: the first is between the product and the agent which is established according to marketing activities. For example, interaction with the price, quality of the product, promotion, place. The second is among the social network of heterogeneous consumer agents where the interaction between consumer agents is caused by the social influence of each agent on other agents (see Fig. 5). To apply this interaction, we have used the preferential attachment social network (Barabási and Albert 1999). The stimulation evolved from these two interaction types significantly affects the purchase preference of the consumer agents as the interaction causes a change in the attitude of consumers with respect to a product.

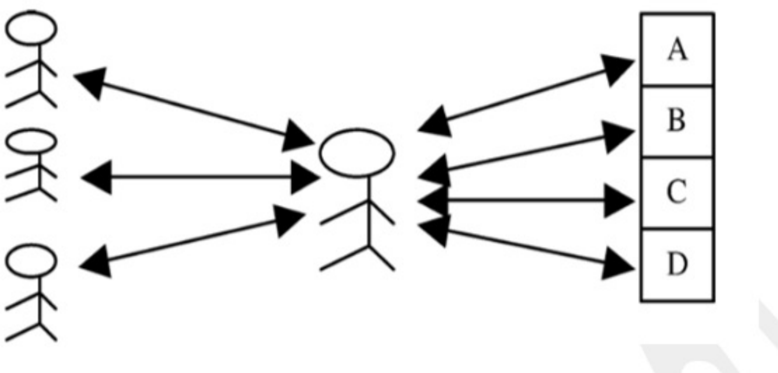


Figure 5: Interactions between (consumer) agents and other (product) agents

The consumer agents' preferences for the product is determined by an algorithmic rule is shown in Fig. 6. The overall pseudo-code of the simulation is provided in Fig. 7 while the entire simulation code and interface is accessible on http://danaye.moeindp.ir/abm.html.

$$IF\ PRE_D \geq TR\ Then\ PRE = PRE_D$$
$$Else\ PRE \neq PRE_D$$
$$IF\ PRE_F \geq TR\ Then\ PRE = PRE_F$$
$$Else\ PRE \neq PRE_F$$
$$IF\ PRE_D \geq TR\ \&\ PRE_F \geq TR$$
$$Then\ PRE = Max\,\{PRE_D, PRE_F\}$$
$$0 \leq PRE_D, PRE_F \leq 1$$
$$TR = 0.5$$

Figure 6: Algorithm which determines consumer agents' preferences for the product

Figure 7: Overall pseudo code of the simulation

Step 0. Create a world 32*32

Step 1. Create agent set based on inputs or total numbers:

- Products:
  - Make 3% of total retails to sell domestic products
  - Make 3% of total retails to sell foreign products
  - Allocate product parameters as their inputs
- Consumers:
  - Set links based on preference attachment network
  - Set social level for any consumer and check the number of consumers according to Table 2
  - Find partner to attach agents
  - Allocate consumer parameters based on their social level and a normal distribution function with average and standard deviation that result from sample data (Table 4)

Step 2. Change or update product parameters

Step 3. Ask consumer to move randomly

Step 4. Make interaction between consumer agents with each other and calculate social index and update PRE function value.

Step 5. Update social network and consumers preferred attachment.

Step 6. Update consumer index for all products.

Step 7. Calculate which consumer Preferred goods or not (Fig. 6)

Step 8. Measure the number of preferences (separately for domestic and foreign).

Step 9. Collect data, plot graph and update outputs.

4.2 Scenarios

We have used the refrigerator local market as a case study to illustrate the influence of interaction between the consumer and product agents on preference decisions. To study the effect of eight parameters used in individual preferences, which are corresponding to *(i)* product marketing mix (4P's) and *(ii)* consumers' sensitivity to them, we analyze different scenarios. Thus, we can observe what happens when we change the product, consumer or environment parameters. In examining those scenarios the preference threshold is set as TR = 0.5.

The observed response variable is the purchase amount of domestic and foreign products under different scenarios which are denoted by superscript letters (d: Domestic; f: Foreign) indicating the type of the product whose marketing mix attribute changes. For example for the *price* attribute they suggest the followings:

D^{d}: total purchases of domestic product brands when domestic product price changes (increases);

D^{f}: total purchases of domestic product brands when foreign product price changes;

F^{d}: total purchases of foreign product brands when domestic product price changes;

F^{f}: total purchases of foreign product brands when foreign product price changes.

We have examined rising changes in the simulation runs (i.e, price increase).

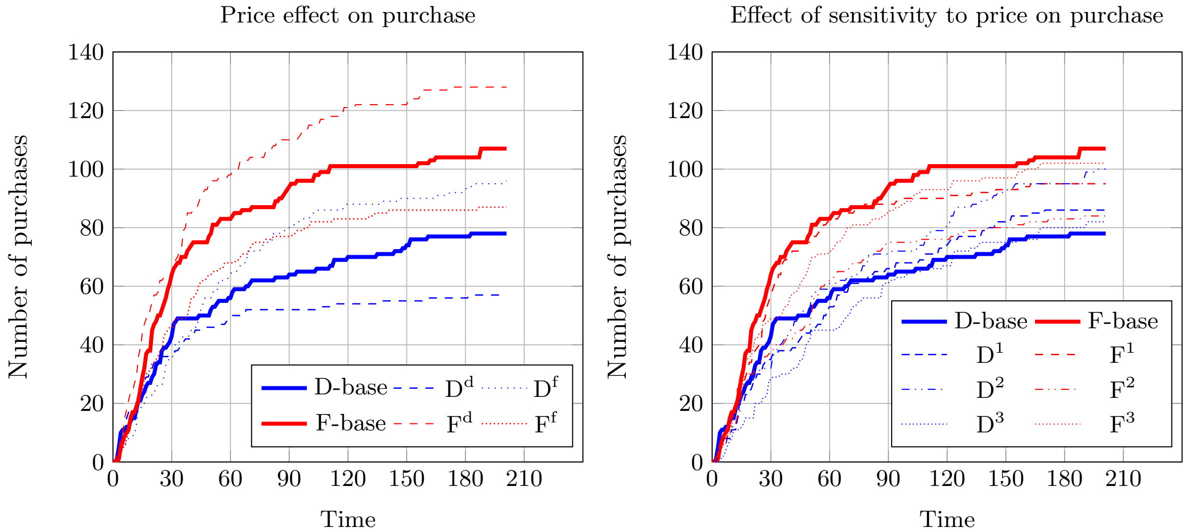
The other scenario determinant is the change in sensitivity of the consumer to each of the marketing mix and they are denoted by superscript numbers (1:low, 2:middle, 3:high) indicating the social class whose sensitivity to a marketing mix attribute changes. For instance, D^2 denotes the total purchases of domestic product brands in a scenario which the sensitivity of middle class consumers to the domestic product price increases. The magnitude of change for all parameters and categories was set as 25% and the effects are discussed under these scenarios in the next sub section.

4.3 Results of sensitivity analysis

We structure our discussions here based on the marketing mix attributes. The visualized and numerical results in this section are obtained by setting the number of consumer agents and simulation time both around 200. The time unit is a proxy to week.

I. *Changes in the product price and consumer sensitivity to price*
As shown in Fig. 8-(a), consumer preferences for foreign or domestic commodities increase when the price of opposite brands rises (see D^{f} and F^{d} vs. their bases). In contrast, the preference for either one drops when the price of the same category increases (see D^{d} and F^{f} vs. their bases). This is partially due to switching the preference to the other product brand and partially because of the affordability. In other words, the accumulated purchases of domestic and foreign brands in either scenario might be less than that of their base.

Sensitivity to the price also has an interesting trend as shown in Fig. 8-(b). The total preference of foreign brands decreases with respect to its baseline if the consumers of any social class become more price-sensitive (see F^1,F^2 & F^3), while the preference of domestic brands are eventually increased (see D^1,D^2 & D^3). This indicates that the market share shifts a bit towards the domestic products when consumers are more sensitive to the price. We can also observe that D^3 and F^3 are quite close to their baselines indicating that the magnitude of the market share will not significantly change if the higher social class becomes more price sensitive. It might be due to the ratio of the population of this class (see Table 2).



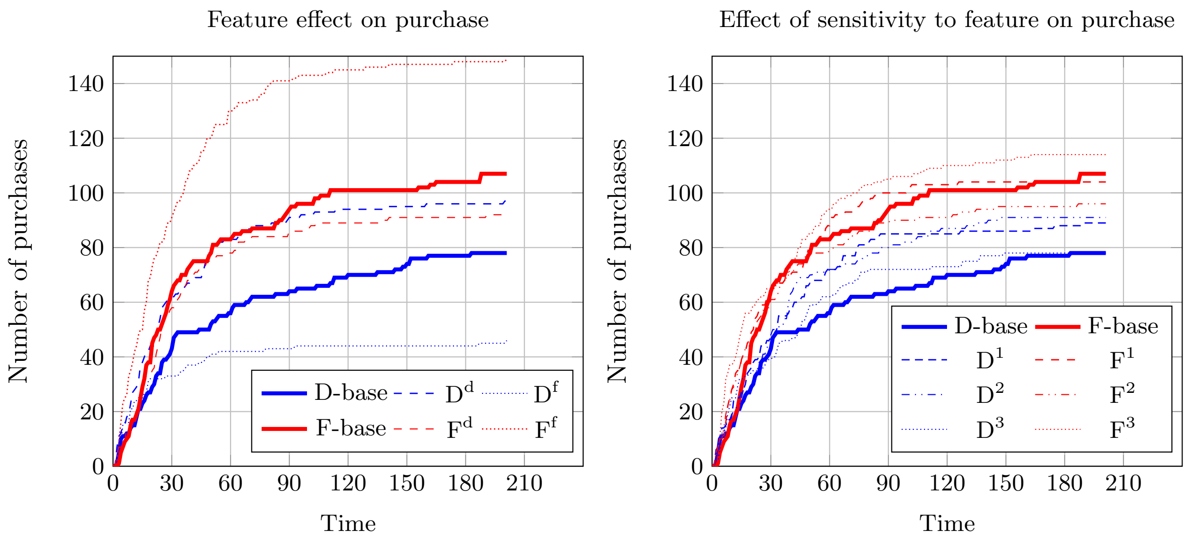
(a) (b)

Figure 8: The simulated effect of rising price and consumers' sensitivity to its change for domestic and foreign products

II. Changes in product features and consumer sensitivity to features

In contrast to price, features and preference of a product have a positive correlation. As shown on Fig. 9-(a) by increase in feature of foreign brands their preference significantly rises and the purchase of domestic ones declines (see F^f & D^f). Similarly, an improvement in feature of the domestic product has positive and negative effect of its own and the foreign brands preference, respectively. However, the magnitude is less. Comparing this figure with Fig. 8-(a) may indicate that investing on features helps more to increase market share for the business owners of the foreign brands.

The trends of preferences with respect to sensitivity of consumers to the feature are shown in Fig. 9-(b). We observe a general increase in domestic purchases for all scenarios, while there is a decline for foreign brands when social class 1 is more sensitive to price. That might be due to *value for money* as this class has less purchase power and therefore, if for any reason the members are doubtful about the durability of the product, they may switch to the cheaper option (domestic).

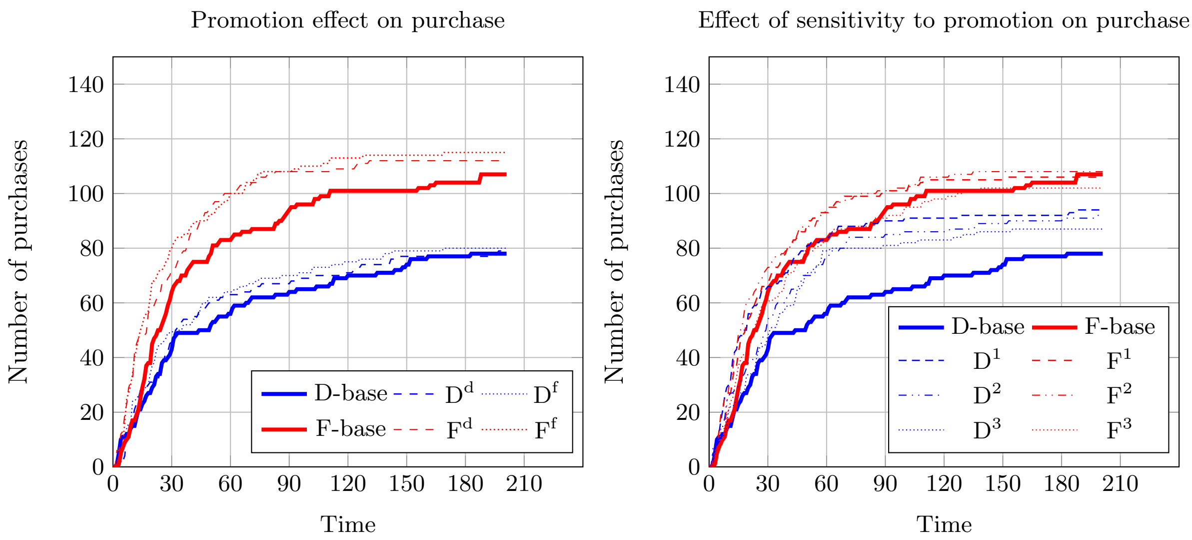


(a) (b)

Figure 9: The simulated effect of rising product feature and consumers' sensitivity to its change for domestic and foreign products

III. Changes in goods promotion and consumer sensitivity to promotion

The effect of advertisement is depicted in Fig. 10-(a). Unsurprisingly, we can observe an increase of both domestic and foreign brands purchased when there is an increase in promotion. The interesting observation here is that the promotion of opposite brands also has a positive effect in purchase preferences (see D^f & F^d) which might be due to social interactions which trigger extra demand. In addition, according to 10-(b) sensitivity of consumers to promotion has more significant effect on purchase of domestic product brands, while the changes for foreign ones is negligible in all scenarios.



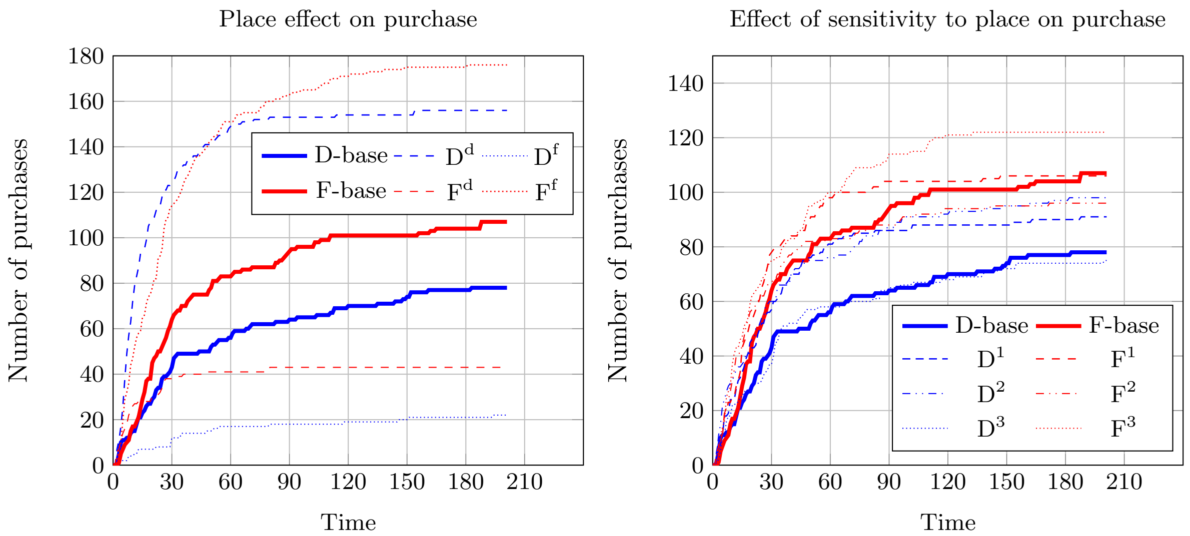
(a) (b)

Figure 10: The simulated effect of rising promotion and consumers' sensitivity to its change for domestic and foreign products

IV. Changes in product place and consumer sensitivity to social influences

Finally, the effect of place (distribution and accessibility) is illustrated in Fig. 11-(a), which shows the most significant change among all marketing mix factors. As shown, the purchase of domestic or foreign brands sharply rises when place is respectively improved for them (see D^d & F^f), while the purchase of the opposite brand drastically drops (see D^f & F^d). This indicates that the preferences are switched from one to the other type.

Regarding the sensitivity of consumers to the place, Fig. 11-(b) depicts that the purchase of domestic brands increases when consumers of the low and middle social classes are more sensitive to place. For the foreign brands it happens for the high class consumers become more sensitive.



(a) (b)

Figure 11: The simulated effect of place and consumers' sensitivity to its change for domestic and foreign products

4.4 Validation and verification

The rigor of an agent-based model is assessed via the *validation* and *verification* process. Validation is referred to the process to show an implemented model corresponds to the reality, while verification is the process of testing the correspondence of an implemented model to the conceptual model. The validation is performed in the analysis stage, and the verification is addressed in the development steps.

We have validated and verified our model following Rand and Rust (2011) methodology wherein the coded model in software is compared with documentation and conceptual model of the study, and mistakes and coding errors are corrected. Then, each part of the program is examined sequentially and errors are rectified. For instance, regarding the preference function, the higher the sensitivity of consumer agents to price is, the greater value of PRE function must be and therefore, the less purchase preference must be made. Any contradicting result to the logical expectation like this might indicate an error.

Further, by assigning different extreme levels of input parameters the overall behavior of the coded model is evaluated and again it is cross checked if the model provides a logical and expected behavior. For example, by setting the preference threshold to the maximum value (tr = 1), consumers should not prefer any product and in contrast, by setting the threshold to the minimum value (tr = 0), all consumers are expected to prefer desired products immediately. The model outputs were observed as expected accordingly for these cases. In addition, we set the domain of the input parameters to their feasible reasonable range to avoid errors in data entry and in case of illegitimate input a message is returned to the user in the interface of the model. For example, the total percentage of people of different classes should be one (or 100%). Otherwise, the model provides a message to users with the corresponding reason for the error.

5 Discussion and conclusion

5.1 Theoretical and practical insights

As mentioned at the beginning, an important fact for product manufacturers and distributors is influencing customers buying preferences. Various models and methodologies have been presented for analyzing, evaluating and providing solutions to this end. They are mainly static and simplistic approaches lacking details to examine issues such as the buyers preferences. This gap can be covered to a good extent using ABM simulation as depicted in this article. Our simulation model includes two main components: *i)* social network, and *ii)* preference function. The social network is the result of the interaction between the consumer agents. Because of the relationship structure between consumers, the preferences attachment network was used as an appropriate network to mimic the communication between customers. In this network any new consumer entering the network, preferably joins to the members who have the most connections. This network was virtually created in the Net Logo software by coding.

The behavior of each member of the network was defined by the preference function in the model. The output of preference function indicates the type of consumer choice (domestic, foreign, neither), while the input variables are defined based on the concept of marketing mix (4Ps). These variables are assigned with coefficients indicating the sensitivity of consumer behavior to them.

Given the fact that there are differences between customers from several aspects, three different social classes were defined and their composition was obtained based on our sample. Then we reflected it to the simulated social network. Other parameters in the social network such as gender, age, etc. may also affect customer preferences.

Community members may have different preferences in different situations. Thus, when consumers enter into new situations created by businesses, they have a different reaction from what they had before. In our case study, similar to Haghighi and Hosseinzadeh (2009) and Nikookar et al. (2009), consumers generally prefer foreign product brands. This preference may alter by changing some of the parameters related to products or consumers resulting in purchase outperformance of domestic product. For instance, if the domestic manufacturers offer new or better features in their product than the past (increasing the feature parameter), provided that all other parameters remain unchanged, more consumers would prefer the domestic products.

Analyzing the simulation model, we observed that if all except the feature value of the domestic and foreign are the same, the preferences of brand with greater feature value is more among the consumers. This pattern happens even if the availability of one of the products is higher than others (for example, when the domestic product is more available than its foreign counterpart). In other words, if the amount of domestic goods distributed in the society is greater than foreign goods and foreign brands are more specific than domestic brands, then the preference of foreign brands still is greater than domestic brands. It indicates that although the quantity of products is important in the market, other variables such as product features (quality, etc.) play a significantly important role as well.

Lei et al. (2022) study air conditioner purchasing preferences in China for different social classes. According to their results, low and middle income class with small houses have rational purchasing preference while low-income class with large houses sits in old fashion and economic preferences. Further, the middle and high income class with small houses have moderate and neutral preference while the high income with small houses show modern pattern of preference. It matches with our results for product price and feature if we consider that the domestic product brands are more affordable but the foreign ones are more modern.

The availability of the product to the consumer is another important factor. If the consumers prefer a product but do not have access to it, they will withdraw and will seek another product. According to our model, if all other conditions are the same, consumers will decide to purchase depending on availability of the product. The higher availability of each item is, the more people will prefer to buy it. According to Figures 8–11, this parameter alters the preference of goods more than other marketing mix. While the distribution or availability of the products are attributed to the 'place' in our study, Sturley et al. (2018) further dig into spatiotemporal drivers of consumer such as store choice, frequency and time of visit. Their ABM simulation captures the trade-off between attractiveness and accessibility in grocery customers' decision making.

Furthermore, members of a community are subject to promotion of products which is is one of the most important ways for interaction between products (or producers) and consumers. As we observed in our model, the more the products are promoted, the more likely the consumers are to purchase. Similarly, Delre et al. (2007) state that promotion plan certainly has a positive effect on the diffusion curve but they further inspect the optimal targeting and timing for the white goods versus brown goods. Promotion can be offered directly by the manufacturer or by the members of a community in a word-of-mouth form which is an indirect advertisement for producers. Although our model implicitly addresses the effectiveness of advertisement, it incorporates the main influencing factors suggested by Cao (1999).

5.2 Limitation and future research

Consumer behavior models generally have many parameters and it is not always practical to collect a full demographic information such as age, gender, marital status, cultural, lifestyle, psychological, etc. to analyze and import them all to analytical models. Our model is not an exception and it was created by overlooking some parameters. In this research, they are limited to the marketing mix (4Ps) while there are various theories regarding the mixing factors of marketing, including 5P, 7P, 9P, etc. Furthermore, the present research is based on the stimulus-reaction model, whereas several models discussed in Section 2 might lead to different results. In addition to the parameters used here, an interesting factor like nationalism for domestic consumption can be added to the model as Shimp and Sharma (1987) report that it is an important factor in buyers choice decision.

The present study has used the income of individuals to identify their social class in the community. This classification can be carried out in different methods or a variety of indicators such as the Gini, Lerner or similar indices. The other possibility is to divide the society into more social classes (five or nine groups based on existing theories).

Finally, the response variable inspected here was limited to two categories of domestic or foreign products, while the same setting might be extendable to consider different brands of it if the meaningful data collection in a larger scale is possible to be inclusive of targeted ones.

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Appendix: Questionnaire

Pairwise comparisons of factors: In buying white-goods which criterion is more important compared to the other. For example if for (price vs. quality) you prefer 'price' select its significance level by the number in the right side of the table.

Table A1: Translated questionnaire

quality	10	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	10	price
Ad	10	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	10	price
Recom.	10	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	10	price
Ad	10	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	10	quality
Recom.	10	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	10	quality
Recom.	10	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	10	Ad

Recom.: recommendations of friends & family

No.	**Questions**	**Brand**	**Responses**				
1	The white goods manufacturer provides after-sale services on time.	D	1	2	3	4	5
		F	1	2	3	4	5
2	Model and aesthetic of products are getting better.	D	1	2	3	4	5
		F	1	2	3	4	5
3	The quality of the products are good.	D	1	2	3	4	5
		F	1	2	3	4	5
4	Guarantee and service of the products are not good.	D	1	2	3	4	5
		F	1	2	3	4	5
5	The products of durable.	D	1	2	3	4	5
		F	1	2	3	4	5
6	The products are not accessible and you should look a lot in the market.	D	1	2	3	4	5
		F	1	2	3	4	5
7	The products are available in big shops.	D	1	2	3	4	5
		F	1	2	3	4	5
8	You can find your product brand in all white-goods shops.	D	1	2	3	4	5
		F	1	2	3	4	5
9	The media acts well in making interest for the product.	D	1	2	3	4	5
		F	1	2	3	4	5
10	I see many of these products in white-goods exhibitions.	D	1	2	3	4	5
		F	1	2	3	4	5
11	There are a lot of advertisements for white goods in social platforms or internet.	D	1	2	3	4	5
		F	1	2	3	4	5
12	Sellers of household products offer good discounts when you buy.	D	1	2	3	4	5
		F	1	2	3	4	5
13	Advertisement for these products is less in TV and newspapers.	D	1	2	3	4	5
		F	1	2	3	4	5
14	Sellers of household products have good attitude with customers.	D	1	2	3	4	5
		F	1	2	3	4	5
15	Friends and family talks about household products with you.	D	1	2	3	4	5
		F	1	2	3	4	5
16	Household products manufacturers and dealers invest a lot for customer relationship.	D	1	2	3	4	5
		F	1	2	3	4	5
17	I usually recommend the the product I buy to others.	D	1	2	3	4	5
		F	1	2	3	4	5
18	I usually talk about price, features, advertisement and penetration of household products to my friends.	D	1	2	3	4	5
		F	1	2	3	4	5
19	I listen to the advice of people before buying.	D	1	2	3	4	5
		F	1	2	3	4	5

1:strongly disagree; 2:disagree; 3:neutral 4:agree 5:strongly agree
D:Domestic; F:Foreign