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Modeling New Product Diffusion in a Competitive Market Using Agent-Based Simulation

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ABSTRACT

The prediction of the results of introducing a new product into the market is one of the vital issues facing the organization's executives before investing in marketing activities. The impact of various factors on the market, as well as the specific characteristics of the market, depending on the region and its product type, has made it difficult to predict market behavior. In Iran, retailers are effective players, especially in the FMCG market. This paper aims to suggest a model for the marketing managers to predict the result of their new product lunch to market considering their special market attributes. Agent-based modeling, as a tool for modeling complicated systems, can be helpful for simulating real-world conditions. In the present paper, agent-based modeling is used to model the market, including retailers and consumers with particular profit functions, and two producers compete with each to maximize their profit. The introduction of a new soft drink in the Iranian market over three years is considered as a case study. The results of policy implementation were evaluated using the decision support system developed in this study. The user interface of this system has been developed with Matlab software, and its model core with SQL Server. The results show that paying attention to the needs of retailers and consumers simultaneously, and changing policies based on long-term profitability, create success in the new product diffusion process. The analysis of a competitive environment, the role of retailers in the market, and the repeat purchase behavior of consumers are instructive. These can provide valuable points for marketing managers to customize the model to their special market and product.

Keywords

Agent-based modeling, New product diffusion, Competitive market, Retailers, Repeat purchase

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1. Introduction

Innovations have become an indispensable factor for securing the long-term success of enterprises (Tseng, 2008). However, multiple factors often affect the success of the innovation diffusion process, which entails high costs for organizations, such that the failure of the diffusion process may sometimes terminate an organization's life. Therefore, it may be vital to anticipate the results of the diffusion of innovation for organizations before introducing their new products to the market.

Innovation diffusion is the process by which an innovation is communicated over time among the participants in a social system (Rogers, 1962). Diffusion models as a tool for predicting the results of innovation diffusion have been largely based on the model suggested by (Bass, 1969). These are usually cumulative models with a macro-level approach to systems, and their development is based on differential equations. These models try to provide simple and overall approximations of systems in the future. Even though these models do not take into the account the heterogeneity of consumers and details of their decision rules and interactions, the biggest problem of these models is that the Bass model requires two of the most important events as inputs that managers would like to predict (Chandrasekaran and Tellis, 2007).

In recent years, simultaneous changes in agent-based modeling and the ability to process large volumes of data make it possible to focus on the details of and diversity in social networks. In agent-based modeling based on a bottom-up approach, the interactions between components and the impact of these interactions on the overall system behavior can also be modeled. Agent-based diffusion models in marketing have mainly been developed since 2000 and provide an appropriate basis for managers to make more accurate decisions. In most practical studies, the basic assumption is that innovations are available to consumers as soon as the diffusion process begins, and the role of intermediary agents such as distributors and retailers in the product diffusion network is considered less. Also, less attention is paid to the competitive environment and the impact of changes on continuing consumer behavior after the primary acceptance of innovations.

The present paper attempts to (i) investigate a competitive environment with two brand owners (producers) and their mutual reactions based on market changes within a game theory structure, (ii) consider the important role of retailers as intermediary players in the market, with rational and profit-seeking decision rules, (iii) and also considers repeat purchase behavior of consumers who continue comparing products before each purchase even when they have previously accepted and used theme.

Continuing the research on new product diffusion process modeling based on agent-based modeling, the present study focuses on fast-moving consumer goods (FMCG), especially on carbonated drinks in the market of Tehran as a retailer-based and price-sensitive market in FMCG goods.

The rest of the paper is organized as follows: Section 2 reviews the existing literature and the research gaps. Section 3 describes the case study. The structure and components of the model and the procedures and parameters of the simulation process are described in section 4. In section 5, we examine the reliability and validity of the model, and in Section 6, the policies are introduced, and the results of the implementation of policies are shown. Finally, the conclusion and recommendations for future research are discussed in section 7.

2. Literature review

The term "diffusion" embraces concepts such as contagion, mimicry, social learning, and organized dissemination Strang and Soule (1998). Diffusion research is an interdisciplinary field rooted in anthropology, sociology, geography, political science, economics, and marketing Kiesling et al. (2012). Ryan and Gross (1943) were the originators of the diffusion paradigm. They found that social contacts, social interaction, and interpersonal communication had an important influence on adopting new behaviors Valente and Rogers (1995). Early efforts to mathematically model the spread of a new product in a marketplace were rooted in analogies from models of epidemics, biology, and ecology (Mahajan and Muller, 1979).

Along these lines, Fourt and Woodlock (1960) developed a simple penetration model to forecast sales of new grocery products. Other studies proposed similar models, but the most influential contribution to date was made by Bass (1969). He specified that an individual's probability of adopting a new product depends linearly on two forces: One that is not related to previous adopters and is represented by the parameter of external influence (traditionally denoted as p, e.g., advertising and mass media); and one that is related to the number of previous adopters, the parameter of internal influence (denoted as q, e.g., word of mouth - WOM) (Goldenberg et al., 2000). Since then, many studies have been done based on the Bass model. Meade and Islam (2006) reviewed the wealth of these studies from a forecasting perspective and concluded that, despite the efforts of many authors, few research questions had been fully resolved. They emphasized that research should include forecasting new product diffusion with

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little or no data and focus on forecasting future behavior instead of estimating the future using past behavior. In the last two decades, many efforts have been made to eliminate the constraints on aggregate models based on the Boss model. Agent-based models, which differ fundamentally from both aggregate differential equations and aggregate simulation approaches such as system dynamics (Milling, 1996), are believed to overcome the problem because of their individual-based modeling approach.

The bottom-up modeling approach can easily incorporate micro-level diversity in adoption, bounded rationality, imperfect information, and individual heterogeneity regarding attributes, behavior, and linkages in social networks (Kiesling et al., 2012).

Agent-based modeling analyzes and implements simple rules of interaction between members. The possibility of combining the effects of these interactions at the macro level enables analysts to model the complexities of social realities, including interactions in the new product diffusion process.

The literature on agent-based models of innovation diffusion is divided into two major streams: theoretical insights and practical applications.

In the field of theoretical findings, research has mainly been carried out in three areas (Kiesling et al., 2012): the impact of consumer heterogeneity on innovation diffusion (Alkemade and Castaldi, 2005; Goldenberg et al., 2000; Delre et al., 2010), the role of social influence in diffusion processes (Delre et al., 2007; Bohlmann et al., 2010; Xiao and Han, 2016) and the effect of promotional marketing strategies on diffusion processes (Delre et al., 2007; Moldovan and Goldenberg, 2004; Goldenberg and Efroni, 2001).

In the field of practical applications, many studies have been done since 2000 that have had a strong influence on the operational use of agent-based models by managers and decision-makers in marketing: In primary studies, such as Berger (2001), the impact of various policies on simulated models with one product is investigated in a non-competitive environment. In subsequent years, attention gradually moved toward the impact of competitive environments in the agent-based models have been seen in (Günther et al., 2011; Kim et al., 2011; Fazeli and Jadbabaie, 2012). Fazeli and Jadbabaie (2012) proposed a game-theoretic analysis of a strategic model of competitive contagion and product adoption in social networks. Of course, in this model, the main players are consumers, not innovation owners, who are, in fact, the main policymakers and competitors in the market.

Paying attention to a subject neglected in research, repeat purchases in competitive environments in (Stummer et al., 2015) simulating the Diffusion of Competing Multi-generation Technologies in Günther and Stummer (2018) and multi-channel choice behavior in Sonderegger-Wakolbinger and Stummer (2015), as the latest effort to fill the gaps in the literature are considered. Of course, the above studies have not addressed the game theory to enter the competition in the model as an effective idea in this area.

The major players in the market, apart from producers and consumers, are retailers. These players have been noticed in a few studies, such as (Heppenstal et al., 2006; Kaufmann et al., 2009; Sturley et al., 2018). Of course, in their proposed models, retailers as agents have no decision-making power or heterogeneity, and they only have a role in determining retail prices. This is despite the fact that retailers are the main factors in the market, and while they compete to attract more consumers, they also have a significant role in determining the availability of products and innovation diffusion. Therefore, they must be entered into diffusion process modeling as important and independent agents. In the past, and by Jones and Ritz (1991), which was a development of the Bass model and did not use agent-based modeling tools, the role of retailers was also considered. That research considered the role of retailers as a precondition (intermediary) of consumers' access to new products.

A review of the literature and existing research gaps show the need to develop a model that considers a competitive environment with active producers as the main policymakers in the market, independent retailers with special profit functions as active agents, and repeat purchase analysis after initial acceptance and the impact of distribution costs in the profit function as important issues in reality. In addition, effective and dynamic reactions to market changes after competitors' entrance of new products show the need for competition approaches to diffusion process modeling. In the present paper, the players are producers who compete in a market in a game theory structure. Also, retailers and repeat purchases and the impact of distribution cost are considered.

Table 1: Practical studies on launching a new product using ABM

Author	Agent-based modeling	Competitive environment	Independent retailers effect	Repeat purchase analysis	FMCG
Berger (2001)	✓	▯	▯	▯	✓
Kaufmann et al. (2009)	✓	▯	▯	▯	✓
Zhang et al. (2011)	✓	▯	▯	▯	▯
Kim et al. (2011)	✓	▯	▯	▯	▯
Xiao and Han (2016)	✓	▯	▯	▯	▯
Heppenstall et al. (2006)	✓	✓	▯	✓	▯
Günther et al. (2011)	✓	✓	▯	✓	▯
Fazeli and Jadbabaie (2012)	✓	✓	▯	✓	▯
Stummer et al. (2015)	✓	✓		✓	▯
Rosales et al. (2018)	✓	▯	✓	✓	▯
Stummer et al. (2021)	✓	▯	✓	✓	▯

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Table 1 lists practical studies on launching a new product using ABM and shows the main topics covered in this article.

3. Case study

This model utilizes the case study of fast-moving consumer goods (FMCG), specifically carbonated drinks. One of the FMGC products was selected for use in the proposed model for the following reasons: the extreme role of retailers in the distribution of these products; the short repurchase period of the products; high rates of the infidelity of consumers to the brands of these products; the possibility of studying competitive policies; and the availability of actual data to evaluate the validity and reliability of the model.

According to statistics from the Majles (Iranian Parliament) Research Center, Iranians imbibe 33 liters per capita of carbonated drinks. Based on an average of 3.5 people per family, that means consumption equal to 1 small can or bottle per day for each family and generalizing the average of the country to Tehran and considering that one producer manages the major shares of the carbonated drink market in Tehran, the consumption parameter of the model is set. From now on, the major brand will be called the old brand, and its producer, as the marketing policy maker, is called the old producer. The new product that starts competing with the main brand when the diffusion process is run is called the new brand, and its producer, as the new producer, makes related marketing policies in the model.

The practical data on new product distribution is extracted from an existing database of archived transactions of a distribution company in Iran for 3 years from the beginning of a carbonated drink lunch period. This information shows the number of purchases made by retailers of the new and old brands, as well as changes in three-year pricing. More details about the case and agents' behavior are described in the next section.

Results of our field research in Tehran shows that in the case of carbonated drink, when the quality of products are similar, price plays a major role in affecting consumer behavior, and the power of loyalty in our field research is 0.34. The power of brand loyalty (POL) is calculated as the ratio between the price of the new brand and the price of the old brand that the consumer chooses the new brand if the ratio is equal or less. Results of field research also show that when the ratio is between POL and 1, the probability of a new brand selection can be calculated from the linear probability distribution function described in formula 2.

4. The proposed model

Based on Rand and Rust (2011), there are seven decisions to be made when designing a model using the ABM approach: Scope of the model, Agents, Properties of the agents, Behaviors, Environment, Input, and output of the model are mentioned throw describing the model in figure 1.

In the proposed model, consumers are agents embedded in a social network communicating with each other and purchasing from their neighbor retailers. Retailers are agents having communicated to their neighbor retailers with the ability to make decisions to purchase from producers and determine retailer price based on their benefits function.

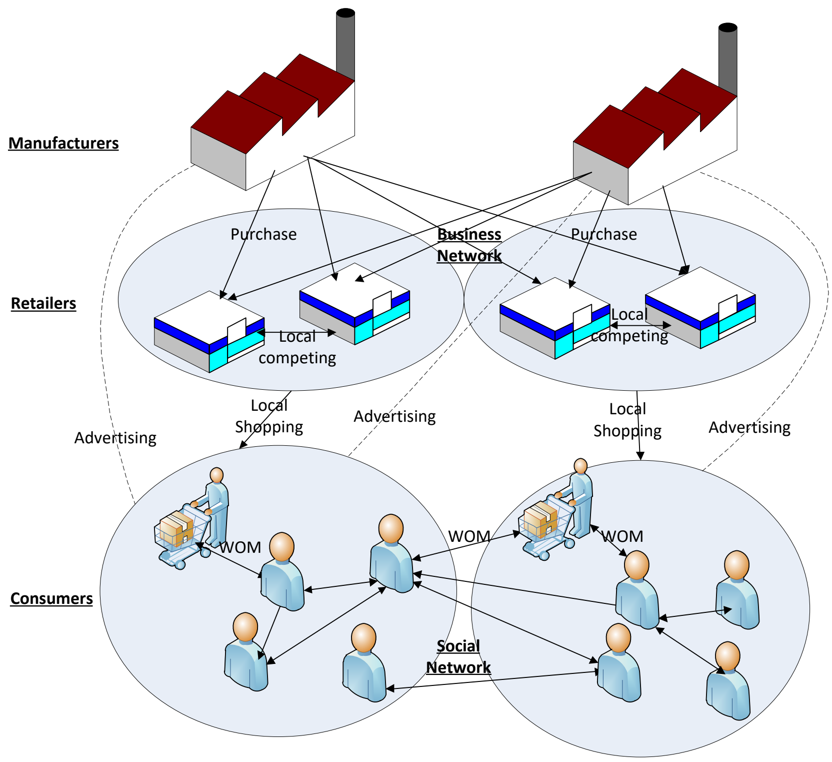

Figure 1: Model Framework

The diffusion process begins with the arrival of a new product to the market while consumers are purchasing the main brand from retailers and retailers from producers. Consumers accept the new product under the influence of external variables (advertising) and internal variables (word of mouth) at a specified rate. Consumers may change retailers because they overcharge compared with their neighboring retailers and also decide which brand to buy based on formula 2.

Retailers also periodically determine product prices based on their previous profit and the lowest prices of neighboring retailers in the market. In this process, they try to simultaneously

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increase their profit and consumers. During the implementation of the model, producers also attempt to change the wholesale price to increase their profits according to information obtained from their profit changes in the past periods and based on specific rules in the game theory structure. In the following sections, the agents, network structure, diffusion process, pricing process, purchasing process, and policies of producers will be described.

4.1. Agents

- Products: In the proposed model, the products are fast-moving consumer goods (FMCG), specifically carbonated drinks.
- Consumers: Households in 22 districts of Tehran whose population is determined based on the 2011 census and based on population and income levels are different.
- Retailers: Business owners who purchase goods from producers or distributors and sell them to end consumers. In Iran, in the case of FMCGs and in terms of the magnitude and diversity of goods, these can be grouped into five types. These retailers also have independent businesses, and their product selection criteria are profit margin, the volume of sales, and the distribution network Miremadi and Faghani (2012). Based on population and income levels in each area, the number and types of retailers are different; these differences are applied in the model. Each type of retailer agent has a different attraction coefficient for probable consumer attraction.
- Producers: They are the brand owners and main policymakers in the model. They apply their policies and change marketing factors, especially wholesale prices in this model, to increase market share and profitability. It is assumed that a producer exists first, and all consumers have been purchasing the product from it. At the start of the diffusion process, a new product enters the market and takes a part of the market share of the primary product, so the main producer is forced to react.

4.2. Network

The social network is in operation for a period of 10,000 days, equivalent to almost 27 years, before the diffusion process begins, based on the model described by Albert and Barabási (2000).

A common property of many large networks is that the vertex connectivity follows a scale-free power-law distribution. This feature is a consequence of the two generic mechanisms that networks expand continuously by adding new vertices and reconnecting vertices in preferred network construction. A model based on these two ingredients reproduces the observed stationary scale-free distributions (Barabási et al., 1999). The network of consumer relationships in our model is constructed by a preferred and gradual approach, consistent with the principles of making pseudo-realistic models.

With the completion of the consumer-consumer network, the construction of the consumer-retailer is created in this way: Consumers in each area are connected to retailers from the same area based on the determined possibility of attracting consumers for each retail type.

Later, when the diffusion process is run, each retailer who is one of the three available retailers for any consumer is periodically evaluated. If there is a better retail price, the retailer may be replaced. This algorithm creates a network in which the right to choose the best retailer is given to the consumer and simultaneously leads retailers to compete to attract more customers.

Now, assuming that the entire network is shaped and all the consumers are buying the main brand, the diffusion process of the new brand in the network can begin.

4.2.1. Diffusion and acceptance process

- The probability of acceptance by each consumer *(i)* in period *(t)* is calculated as follows: (Amini et al., 2012).

$$p(i,t) = 1 - (1 - p) \prod_j (1 - q_j) \tag{1}$$

- In the above formula, p is the probability for consumer (*i*) that is influenced by external advertisement, and q is the probability of consumer (*i*) that is influenced by word of mouth of accepted consumers *(j)*. These values are entered into the proposed model based on the amounts specified in Sultan et al. (1990): p=0.03, q=0.4. Later, verification tests on results show that the implementation of the model with these parameter values is robust, and they are matched to the real data.
- In the process of acceptance, only individuals who consume the product can have an impact on other individuals. So, not only should they first accept the new product, but also, based on the model described by Jones and Ritz (1991), the product should exist in one of their retail centers, and they should buy the product from the retailer at least once.

4.2.2. Consumer buying process from the retailer

As mentioned, the retailers a consumer selects are determined in each period of the model so that the consumer can go to one of the retailers in the consumer's home region in each period. Assuming that the consumer knows there is a new brand of product (the adoption process is complete), the price of the new brand is lower than the main brand, and the new brand is available in stores, the new brand is selected by the consumer by the following probability formula called brand selection probabilistic function in the present paper:

P (New Brand Selection) = (Old rp- New rp)/(Old rp – POL)
Where Old rp >= New rp (2)
Else P (New Brand Selection) = 0

P (Old Brand Selection) = 1- P (New Brand Selection) (3)

Where "Old rp" and "New rp" are the retailer prices of the main brand and new brand, respectively, and "POL" is consumer power of loyalty to the main brand.

4.2.3. Retailer pricing process

- The producers can only determine wholesale prices, which are the sale prices of the products to the retailers by the producers. Wholesale prices are determined based on policies set by producers.
- Each retailer in the model determines the retail price in this paper, and it is based on an algorithm referred to in (Heppenstal et al., 2006) as the Pricing Algorithm:
  - If the profit is rising, continue implementing the last price change;
  - If the profit is falling, increase the price.
  - If this does not work, decrease the price.
  - If the profit is constant (within a defined tolerance), keep the price constant.

The retailers periodically implement the above requirements, and appropriate decisions are made. The retailers also periodically check other retailers' prices and set the price close to the lowest region price based on a defined algorithm in the model.

4.2.4. Retailer buying process from producers

Each producer's sales agent visits the assigned retailers to sell his products in a specific period. The retailers determine the share of each brand on their shelves based on the income derived from each brand. This income is affected by the (i) consumer purchases and (ii) the retailer's profit margin. When producers' sales agents come, retailers order the amount of product based on the share of space for each brand, excluding the brand inventory on the shelf.

4.2.5. Producers' policies

It is assumed that each producer can change the value of marketing parameters such as the wholesale price, the proposed retail price, the amount and coverage area of advertising, the product distribution areas, and the visiting period to retailers to increase market share and profits. To simplify policymaking, only the prices are changed in different policies; other parameters are set at constant values. In the first step of policymaking, the initial wholesale and retail prices are set, and the results are checked. It should be noted that retailers change the retail prices of both brands during the model implementation; the values set at the beginning of model implementation are only the initial values suggested by the producers and have no control over retail price changes. Also, none of the producers can change the values of the model parameters during the model implementation. Later, in a competitive environment and according to information the producers receive from their situation in the market, each producer changes its wholesale price intending to increase its profit during the model implementation. The rule for determining the wholesale price is based on the algorithm used by the retailers.

5. Model test

A large number of independent and effective agents, complex and local interactions between agents, the impact of time in simulation results, and the dynamics in the system are some properties of our problem. Rand and Rust (2011) explain that the exhibition of these properties in the problem confirms that ABM is an appropriate solution for the problem and one of very few approaches that works.

5.1. Verification

Two experts compared the code with the model plan and verified the validity of the proposed model. In addition, corner case, sampled case, specific scenario, and relative value testing were carried out; the results confirmed the model's validity.

5.2. Validation

Validation is the process of determining how well the implemented model corresponds to reality. Four steps were taken to ensure rigor in validation:

1. Micro-face validation: Experts in the field of FMCG approved the utilization of the Pricing Algorithm introduced by Heppenstall et al. (2006) when a producer and a retailer faced a change in profit and sales. The retailers' behavior in the purchasing process, Consumer buying process from retailers, and Retailer pricing process were also approved.
2. Macro-face validation: the behavior of factors such as purchase and sale levels, wholesale price and retailer price, and also market share of the brands were evaluated. The difference between estimated factors and their real values was compared using the Theil-Sen method, and the cumulative behavior pattern of the model was confirmed.
3. Empirical input validation: The accuracy of input data such as population, price, and costs and their adaptation to the real data were confirmed.
4. Empirical output validation: Total sales were evaluated as one of the main outputs where input data were adapted to the corresponding real data.
5. Cross-model validation: It was performed by comparing our results both to the modified bass model formulated by Jones and Ritz (1991) and the basic bass model.

Four parameters of the model as input and correlation between results and the basic bass model and also real data as outputs are presented in table 2.

Table 2: correlation between results and conceptual model and real data

p_{BA} Probability of adding new vertices in preferred network construction	q_{BA} Probability of reconnecting vertices in preferred network construction	P probability of external effect in the acceptance process	Q probability of internal effect in the acceptance process	correlation between model acceptance rate and the Bass model (R2)	correlation between retailers' purchase ln model result and related real data (R2)
0.8	0.1	0.03	0.37	0.988	0.854
0.7	0.1	0.03	0.37	0.983	0.741
0.4	0.1	0.03	0.37	0.99	0.325
0.8	0.15	0.03	0.37	0.971	0.540
0.8	0.1	0.01	0.37	0.989	0.582
0.8	0.1	0.05	0.37	0.989	0.658
0.8	0.1	0.03	0.30	0.971	0.301
0.8	0.1	0.03	0.45	0.987	0.455

6. Model implementation

After verification and validation of the model, its parameters were set based on four policies, and the model was run. In these policies, the wholesale price and retail price of the main brand were fixed, and the prices for the new brand in each policy were set differently. Parameter values and results were as follows:

6.1. Fixed parameter values in pricing policies

- Model implementation period: equal to 1,000 days
- Impact of advertising: p=0.03
- Effect of WOM: q=0.4
- Period of change in the retail price: 45 days
- Period of retailer change by customer: 15 days
- Sales visits period for the main product and new product: 15-day period with a delay of 3 days
- Period and type of advertising: television advertising for the new product for 30 days from the beginning of the model implementation
- Advertising cost per day: 300 million rials
- Product distribution to the retailer: distribution in all regions and to all retailers is done from the beginning of the simulation for both products
- Distribution cost for each customer: 50,000 rials
- Loyalty power of main product: set at 0.34.

Table 3 shows the names of the policies and the values of the variables in policy development.

Table3: Policy values

Policy number	Policy name	New brand			Main brand		
		Cost price	Wholesale price	Retail price	Cost price	Wholesale price	Retail price
1	Balance price	4	6.5	8	4	8.5	10
2	Regardless of retailers' profit	4	7.5	8	4	8.5	10
3	Attention to consumers	4	6.5	7	4	8.5	10
4	Decrease profit and attention to retailers	4	5.5	8	4	8.5	10

NOTE: Values shown in thousands of Rial

Figures 2 to 5 present the cumulative monthly (30-day period) simulation results for each policy by displaying profit and sales for each product.

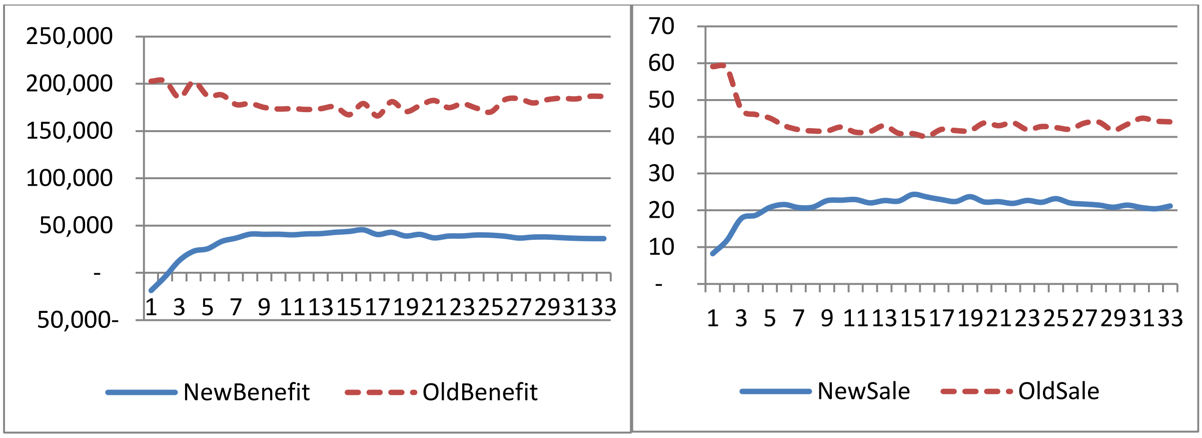

Figure2: Profit and sales for policy 1 (balance price)
NOTE: Profit: millions of Rial; sales: millions of cans.

The balanced policy considers both the retailers' profit and consumers' sensitivity to price. The simulation results show that the new brand achieves suitable and constant profit in the long term.

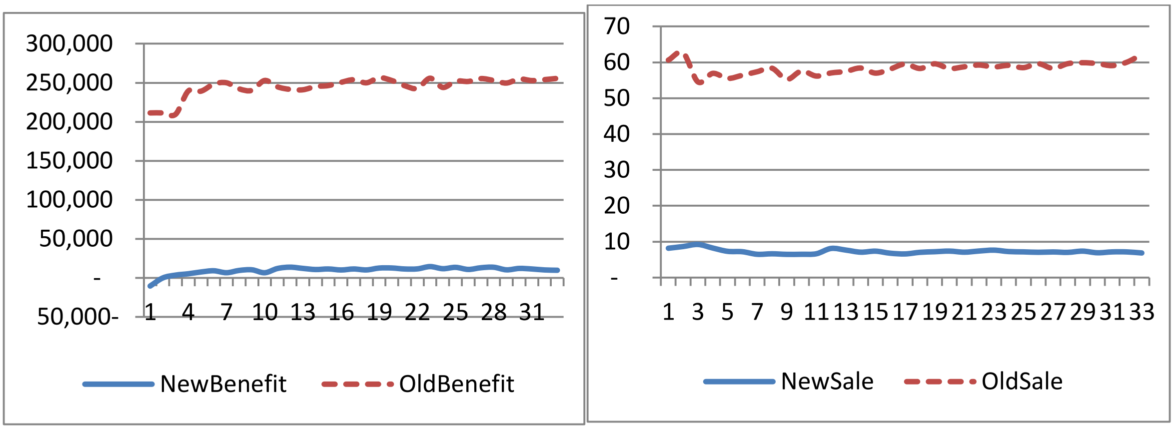

Figure 3: Profit and sales for policy 2 (regardless of the retailer's profit)
NOTE: Profit: millions of Rials; sales: millions of cans.

This is an expediency policy under which the new producer tries to allocate part of the retailers' profit to itself. In this case, retailers avoid allocating adequate space to the product themselves until the retail price increases enough to achieve optimum profit because of a high wholesale price and low profit for the retailers. As a result, although the new producer uses advertising to provide enough information to consumers to increase the population of adopters and assign the right retail price for consumers, lack of access to the new brand for consumers leads the new producer to don't achieve a high market share and appropriate profit.

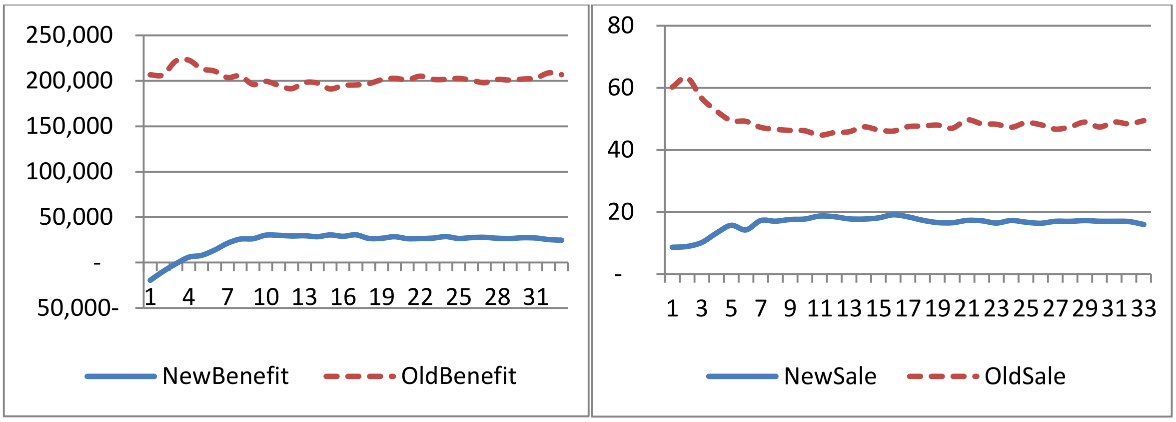

Figure 4: Profit and sales for policy 3 (attention to consumers)

NOTE: Profit: millions of Rials; sales: millions of cans.

This is a policy of high interest to consumers, in which the primary retail price set by the producer is decreased to attract consumers' attention. But it can be seen that retailers gradually increase the retail price because of their low profit and the possibility of retail price increment. In fact, retailer price reduction has a negative effect on retailers' profit and their purchase amount in the initial steps of the diffusion process, which leads to a lack of enough inventory of the new brand on retailer shelves. In other words, despite enough investment in advertising by the producer, there is no product to be bought by adopters, and the total profit of the new producer is lower in policy 3 compared to policy 1.

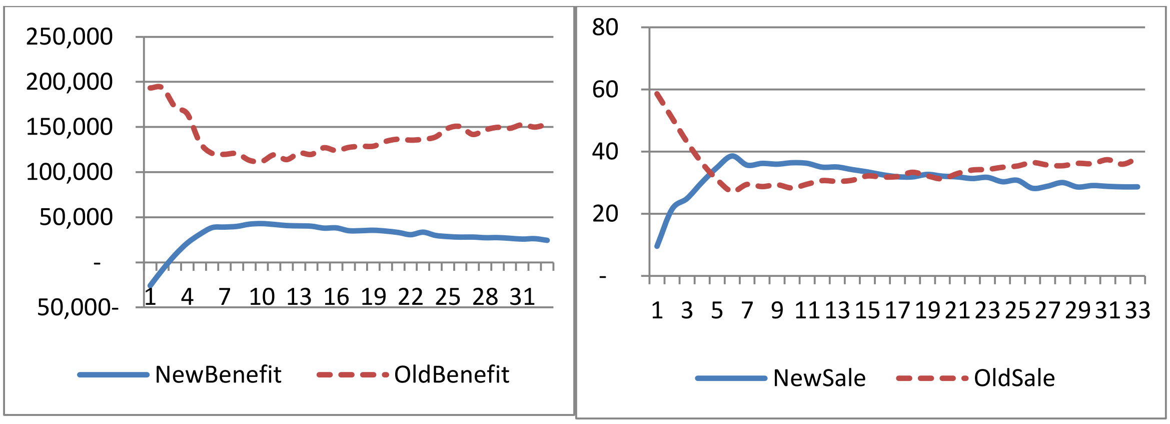

Figure 5: Profit and sales for policy 4 (decrease profit and attention to retailer)

NOTE: Profit: millions of Rials; sales: millions of cans.

In this policy, the main attention is on the retailers. The new producer reduces its profit by keeping a low wholesale price, which causes an increment in retailers' profit and determines a rational initial retail price for consumers. In this case, due to the high incentive of retailers and consumers to buy the new brand, seizing market share happens more quickly than in the other policies, and the new product gets 50% of the market share. However, because of the decline in the wholesale price and the reduction of profit for each product for the producer, despite the increment in sales amount, the total profit achieved doesn't increase and is equal to the first policy. This is despite the fact that if the sales amount decreases, as happened later, the risk of losing the benefit will be higher.

6.2. Changing producers' policies using game theory

Applying game theory to the model, producers can change their policies under changing profits and market conditions. After applying these changes in the model, the four policies were implemented again. After the changes, the wholesale prices for each brand in each policy are not just the initial value, and both producers can change the parameters during the model implementation. They can see the results, and in order to improve their profit function, they can decide to change the values of the wholesale prices. In this game, the players are the producers. Each game period is a 45-step simulation, and the decision of each player is determined based on the observation of profit changes in the previous two periods based on the Pricing Algorithm (Heppenstall et al., 2006) performed for retailer pricing before. Each player uses the algorithm to make the decision to change or maintain its wholesale price at the next level.

6.3. How do player actions affect the system, and what are the results?

Changes in the wholesale prices, which are the retailers' purchase costs, result in changes in retailers' profit margin and force them to react. Their reaction affects consumer behavior which in turn affects the Retailers' pricing decision and also their purchase behavior from producers. In fact, these changes are a result of wholesale price changes made by the producers, which has turned them into a casual loop. Changes in the sales and profit of the producers as changes in their situation in a game lead to their reactions in subsequent periods of the game. Because of the number of influencers and their type and timing effect, a complex game occurs between producers to increase their own market share and profit. What's interesting is that in the real world, similar to the same game, which details are illustrated in figure 6. The casual loop below is approved by 10 experts, including marketing researchers and business managers in Iran.

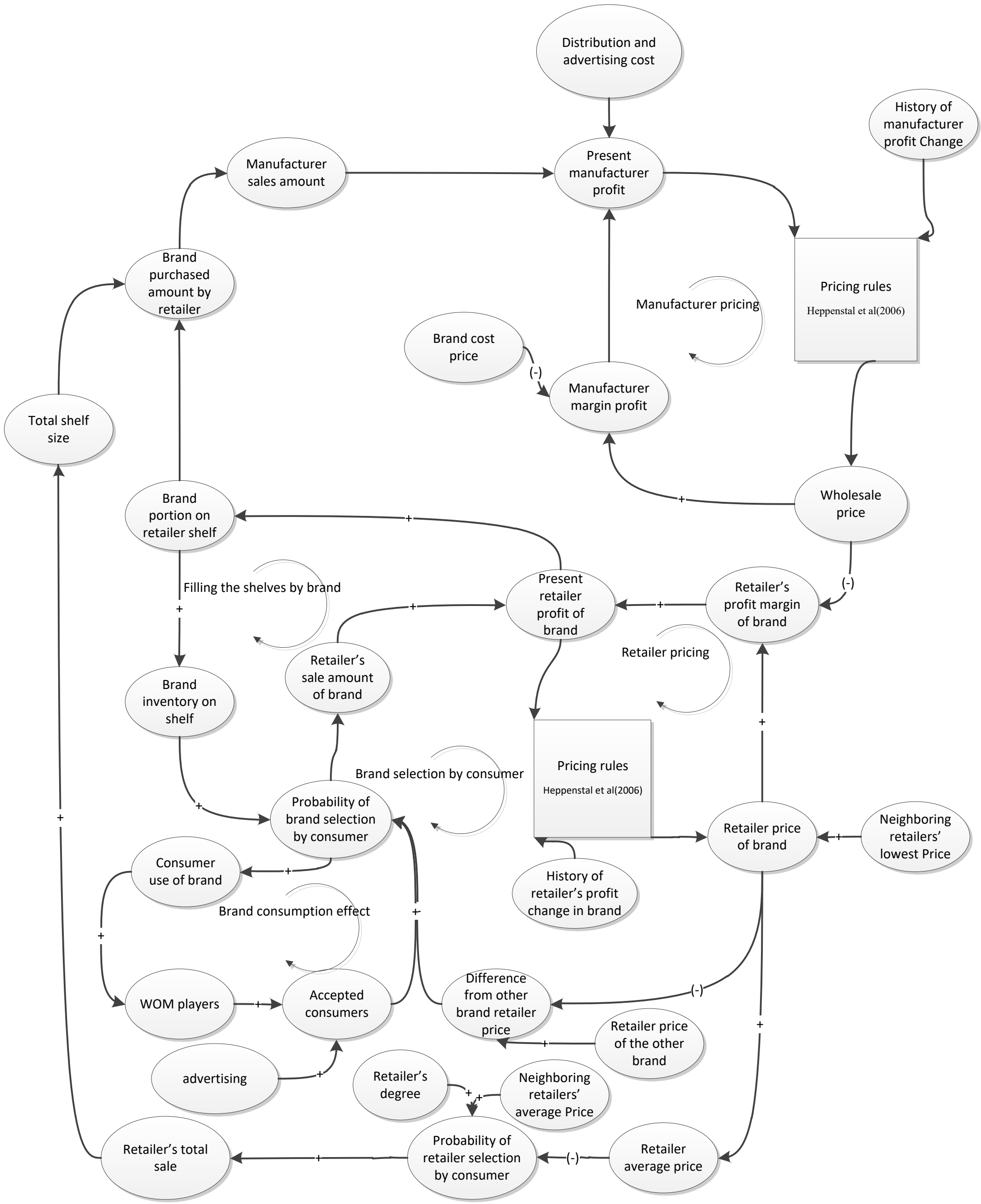

Figure 6: Casual chart for the model

It should be noted that producers throughout the game are aware only of their own sales and profits, and they react based only on their own situation, not the competitor's situation.

The profit function in each period is the net profit from the sale of the product by the producer during that period. It is calculated by the following formula:

$$\text{Gross profit} = (\text{wholesale price} - \text{manufacturing actual cost}) * \text{total sales} \tag{4}$$

$$\text{Net profit} = \text{gross profit} - (\text{advertising cost} + \text{distribution cost}) \tag{5}$$

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After running the model for more than 1,000 periods, the total net profit obtained for each producer was calculated and displayed in the following table. It appears that after this period, the game has reached a balance condition because the situation of both producers is almost constant, and any reaction to a competitor's change may lead to a deterioration in profit. Table 4 shows the long-term results for each policy under a Nash equilibrium for the game.

Table 4 Long term result for each policy

Old Brand Benefit	New Brand Benefit	Policies
6,278,354,837	1,294,564,762	Policy 1
9,146,220,072	143,977,855	Policy 2
4,336,280,741	1,027,191,329	Policy 3
3,886,442,076	639,161,141-	Policy 4

Figures 7 to 10 show the results of the implemented policies after the application of game theory.

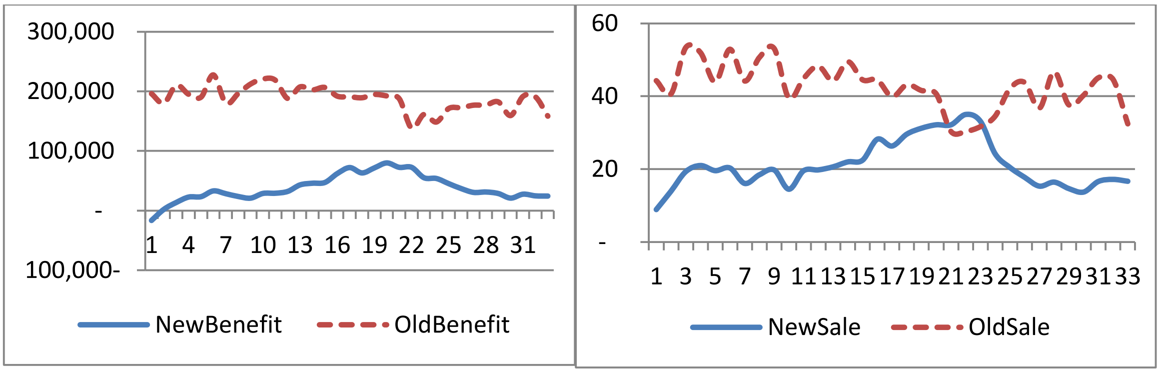

Figure 7: Profit and sales in policy 1 after application of game theory (decrease profit and attention to retailer)
NOTE: Profit: millions of rials; sales: millions of cans.

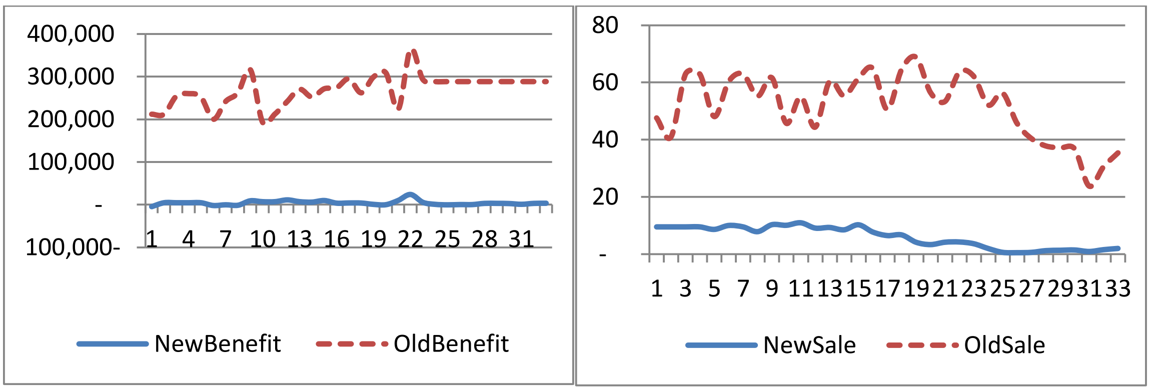

Figure 8: Profit and sales for policy 2 after application of game theory (regardless of the retailer's profit)
NOTE: Profit: millions of rials; sales: millions of cans.

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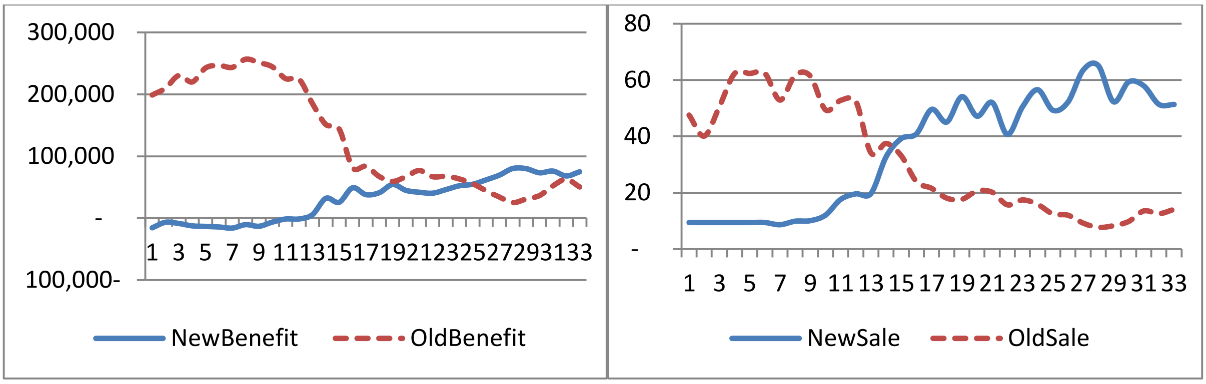

Figure 9: Profit and sales for policy 3 after application of game theory (attention to consumers)
NOTE: Profit: millions of rials; sales: millions of cans.

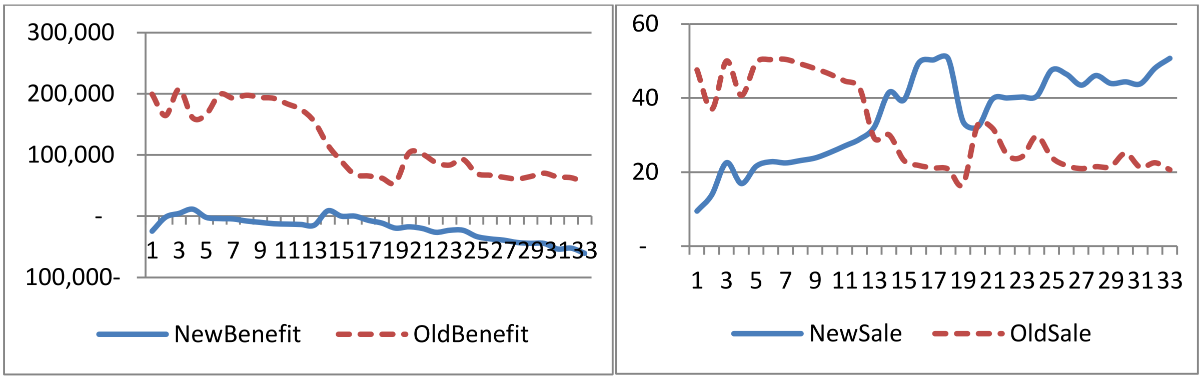

Figure 10: Profit and sales for policy 4 after application of game theory (decrease profit and attention to retailer)
NOTE: Profit: millions of rials; sales: millions of cans.

In policy 1, the new producer achieves the same profit gained before incorporating game theory into the model but with more fluctuations. In policy 2, there is not much difference in the results, but fluctuations are created for the main producer. In policy 3, the reactions of the main producer lead to profit reductions for him, while there are no changes in the results for the new producer. If the main producer does not react, its situation would be better. Policy 4, which apparently can be appealing to a new producer, in fact, is destructive and dangerous for both of them.

It is clear from the above results that policy 1 is the best; it simultaneously achieves a reasonable profit and market share for the new producer.

7. Conclusion

The present article attempts to examine issues that previous researchers did not pay enough attention to them at the same time (see Table 1). These include competitive environments, the effective role of retailers in the publishing process, repeat purchases after initial acceptance of innovation, and consideration of FMCG features in launching a new product. An agent-based model was proposed, considering different market decision-makers to cover the mentioned gaps. The agents are consumers who make decisions to stay loyal to brands and retailers in their shopping; Retailers, who have their own profit-based decision rules for repurchasing and pricing products they sell to consumers and compete with each other to attract more consumers; and producers, who have specific decision rules in competition with others to gain more market share and profit. After the construction of a communication network between consumers and retailers and within themselves, based on the principles of preferred networks, the model was run for 1,000 periods, and the behavior of consumers and retailers was simulated and evaluated. At the same time, competition between producers to increase their profits and the results of different policies for a new producer in a dynamic competitive environment were evaluated. The results show that to accurately predict the results of the launch of a new product, in addition to considering the principles of diffusion models, the behavior of key players in the post-release period and in the market repurchase process must be considered. Also, decisions about whether to implement any changes should consider the fact that the effect of changes in the market is not linear but is the result of decisions made by different decision-makers at different levels. The present paper aimed to find the best policy for a producer who wants to launch a new product into the market when a similar product is already in the market. The results show that disregarding retailers is problematic in the diffusion process, and paying attention only to consumers can be catastrophic.

From the managerial aspects of the results of this study, it can be pointed out that for the successful launch of a new brand, depending on the price and position of competitors, the interests of retailers and consumers must be considered simultaneously. The developed DSS software can also be used by administrators as a tool to adjust parameter values such as margins and costs.

The present paper discusses only the effect of wholesale price changes by producers. Future research could consider other factors such as timing, amounts, and media advertising coverage regions. In addition, in the present paper, the target areas for product distribution by producers, sales visit periods, and product shipment to retailer costs were assumed to be constant, which could be considered in implementing a policy in the proposed and similar models. Finally, it is suggested that this model be developed, including more producers.

References

Albert, R. and Barabási, A.L., 2000. Topology of evolving networks: local events and universality. *Physical review letters*, *85*(24), pp. 5234-5237. https://doi.org/10.1103/PhysRevLett.85.5234.

Alkemade, F. and Castaldi, C., 2005. Strategies for the diffusion of innovations on social networks. *Computational Economics*, *25*(1), pp.3-23. https://doi.org/10.1007/s10614-005-6245-1.

Amini, M., Wakolbinger, T., Racer, M. and Nejad, M.G., 2012. Alternative supply chain production–sales policies for new product diffusion: An agent-based modeling and simulation approach. *European journal of operational research*, *216*(2), pp.301-311. https://doi.org/10.1016/j.ejor.2011.07.040.

Barabási, A.L. and Albert, R., 1999. Emergence of scaling in random networks. *science*, *286*(5439), pp.509-512. https://doi.org/10.1126/science.286.5439.509.

Bass, F.M., 1969. A new product growth for model consumer durables. *Management science*, *15*(5), pp.215-227. https://doi.org/10.1287/mnsc.15.5.215.

Berger, T., 2001. Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural economics*, *25*(2-3), pp.245-260. https://doi.org/10.1111/j.1574-0862.2001.tb00205.x.

Bohlmann, J.D., Calantone, R.J. and Zhao, M., 2010. The effects of market network heterogeneity on innovation diffusion: An agent-based modeling approach. *Journal of Product Innovation Management*, *27*(5), pp.741-760. https://doi.org/10.1111/j.1540-5885.2010.00748.x.

Chandrasekaran, D. and Tellis, G.J., 2007. A critical review of marketing research on diffusion of new products. *Review of marketing research*, *3*, pp.39-80. https://doi.org/10.1108/S1548-6435(2007)0000003006.

Delre, S.A., Jager, W. and Janssen, M.A., 2007. Diffusion dynamics in small-world networks with heterogeneous consumers. *Computational and Mathematical Organization Theory*, *13*(2), pp.185-202. https://doi.org/10.1007/s10588-006-9007-2.

Delre, S.A., Jager, W., Bijmolt, T.H. and Janssen, M.A., 2010. Will it spread or not? The effects of social influences and network topology on innovation diffusion. *Journal of Product Innovation Management*, *27*(2), pp.267-282. https://doi.org/10.1111/j.1540-5885.2010.00714.x.

Fazeli, A. and Jadbabaie, A., 2012, December. Game theoretic analysis of a strategic model of competitive contagion and product adoption in social networks. In *2012 IEEE 51st IEEE Conference on Decision and Control (CDC)* (pp. 74-79). IEEE.

Fourt, L.A. and Woodlock, J.W., 1960. Early prediction of market success for new grocery products. *Journal of marketing*, *25*(2), pp.31-38. https://doi.org/10.1177/002224296002500206.

Goldenberg, J. and Efroni, S., 2001. Using cellular automata modeling of the emergence of innovations. *Technological Forecasting and Social Change*, *68*(3), pp.293-308. https://doi.org/10.1016/S0040-1625(00)00095-0.

Goldenberg, J., Libai, B., Solomon, S., Jan, N. and Stauffer, D., 2000. Marketing percolation. *Physica A: statistical mechanics and its applications*, *284*(1-4), pp.335-347. https://doi.org/10.1016/S0378-4371(00)00260-0.

Günther, M. and Stummer, C., 2018. Simulating the diffusion of competing multi-generation technologies: An agent-based model and its application to the consumer computer market in Germany. In *Operations research proceedings, 2016,* Springer, Cham. pp. 569-574. https://doi.org/10.1007/978-3-319-55702-1_75.

Günther, M., Stummer, C., Wakolbinger, L. M., and Wildpaner, M., 2011. An agent-based simulation approach for the new product diffusion of a novel biomass fuel. *Journal of the Operational Research Society*, *62*(1), pp. 12-20. https://doi.org/10.1057/jors.2009.170.

Heppenstall, A., Evans, A. and Birkin, M., 2006. Using hybrid agent-based systems to model spatially-influenced retail markets. *Journal of Artificial Societies and Social Simulation*, *9*(3). Available at: https://www.jasss.org/9/3/2.html.

Jones, J.M. and Ritz, C.J., 1991. Incorporating distribution into new product diffusion models. *International Journal of Research in Marketing*, *8*(2), pp.91-112. https://doi.org/10.1016/0167-8116(91)90018-3.

Kaufmann, P., Stagl, S. and Franks, D.W., 2009. Simulating the diffusion of organic farming practices in two New EU Member States. *Ecological Economics*, *68*(10), pp.2580-2593. https://doi.org/10.1016/j.ecolecon.2009.04.001.

Kiesling, E., Günther, M., Stummer, C. and Wakolbinger, L.M., 2012. Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, *20*(2), pp.183-230. https://doi.org/10.1007/s10100-011-0210-y.

Kim, S., Lee, K., Cho, J.K. and Kim, C.O., 2011. Agent-based diffusion model for an automobile market with fuzzy TOPSIS-based product adoption process. *Expert Systems with Applications*, *38*(6), pp.7270-7276. https://doi.org/10.1016/j.eswa.2010.12.024.

Mahajan, V. and Muller, E., 1979. Innovation diffusion and new product growth models in marketing. *Journal of marketing*, *43*(4), pp.55-68. https://doi.org/10.1016/j.ijresmar.2009.12.012.

Meade, N. and Islam, T., 2006. Modelling and forecasting the diffusion of innovation–A 25-year review. *International Journal of forecasting*, *22*(3), pp.519-545. https://doi.org/10.1016/j.ijforecast.2006.01.005.

Milling, P.M., 1996. Modeling innovation processes for decision support and management simulation. *System Dynamics Review: The Journal of the System Dynamics Society*, *12*(3), pp.211-234. https://doi.org/10.1002/(SICI)1099-1727(199623)12:3<211::AID-SDR105>3.0.CO;2-8.

Miremadi, A. and Faghanie, E., 2012. An empirical study of consumer buying behavior and its influence on consumer preference in Iranian FMCG market: A case study. *International Business and Management*, *5*(1), pp.146-152. https://doi.org/10.3968/J.IBM.1923842820120501.1115.

Moldovan, S. and Goldenberg, J., 2004. Cellular automata modeling of resistance to innovations: Effects and solutions. *Technological Forecasting and Social Change*, *71*(5), pp.425-442. https://doi.org/10.1016/S0040-1625(03)00026-X.

Rand, W. and Rust, R.T., 2011. Agent-based modeling in marketing: Guidelines for rigor. *International Journal of research in Marketing*, *28*(3), pp.181-193. https://doi.org/10.1016/j.ijresmar.2011.04.002.

Rogers, E. M. 1962, Diffusion of Innovations, Free Press, New York.

Rosales, C.R., Whipple, J.M. and Blackhurst, J., 2018. The impact of distribution channel decisions and repeated stockouts on manufacturer and retailer performance. *IEEE transactions on engineering management*, *66*(3), pp.312-324. https://doi.org/10.1109/TEM.2018.2835653.

Ryan, B. and Gross, N.C., 1943. The diffusion of hybrid seed corn in two Iowa communities. *Rural sociology*, *8*(1), pp.15-24.

Sonderegger-Wakolbinger, L.M. and Stummer, C., 2015. An agent-based simulation of customer multi-channel choice behavior. *Central European Journal of Operations Research*, *23*(2), pp.459-477. https://doi.org/10.1007/s10100-015-0388-5.

Strang, D. and Soule, S.A., 1998. Diffusion in organizations and social movements: From hybrid corn to poison pills. *Annual review of sociology*, *24*(1), pp.265-290. https://doi.org/10.1146/annurev.soc.24.1.265.

Stummer, C., Kiesling, E., Günther, M. and Vetschera, R., 2015. Innovation diffusion of repeat purchase products in a competitive market: An agent-based simulation approach. *European Journal of Operational Research*, *245*(1), pp.157-167. https://doi.org/10.1016/j.ejor.2015.03.008.

Stummer, C., Lüpke, L. and Günther, M., 2021. Beaming market simulation to the future by combining agent-based modeling with scenario analysis. *Journal of Business Economics*, *91*(9), pp.1469-1497. https://doi.org/10.1007/s11573-021-01046-9.

Sturley, C., Newing, A. and Heppenstall, A., 2018. Evaluating the potential of agent-based modelling to capture consumer grocery retail store choice behaviours. *The International Review of Retail, Distribution and Consumer Research*, *28*(1), pp.27-46. https://doi.org/10.1080/09593969.2017.1397046.

Sultan, F., Farley, J.U. and Lehmann, D.R., 1990. A meta-analysis of applications of diffusion models. *Journal of marketing research*, *27*(1), pp.70-77. https://doi.org/10.1177/002224379002700107.

Tseng, F. M., 2008. Quadratic interval innovation diffusion models for new product sales forecasting. *Journal of the Operational Research Society*, *59*(8), pp.1120-1127. https://doi.org/10.1057/palgrave.jors.2602457.

Valente, T.W. and Rogers, E.M., 1995. The origins and development of the diffusion of innovations paradigm as an example of scientific growth. *Science communication*, *16*(3), pp.242-273. https://doi.org/10.1177/1075547095016003002.

Xiao, Y. and Han, J., 2016. Forecasting new product diffusion with agent-based models. *Technological Forecasting and Social Change*, *105*, pp.167-178. https://doi.org/10.1016/j.techfore.2016.01.019.

Zhang, T., Gensler, S. and Garcia, R., 2011. A study of the diffusion of alternative fuel vehicles: An agent-based modeling approach. *Journal of Product Innovation Management*, *28*(2), pp.152-168. https://doi.org/10.1111/j.1540-5885.2011.00789.x.