Agent-based modeling and simulation in the analysis of e-commerce market

Muhammad Umar Farooq, Fahim Gohar Awan
Department of Electrical Engineering, University of Engineering & Technology, Lahore.
mufarooq40@gmail.com, fawan@uet.edu.pk

***Abstract*—A paradigm shift from physical to e-commerce market demands a prudent marketing strategy for online brands to survive in a vying environment. A newbie must be aware of challenges, they may face while introducing their brand in virtual market. With evolution of technology and introduction of fairly powerful computers, modeling and simulation techniques have become very popular to envision upcoming challenges. Many techniques have been introduced to model different real-world problems to date. Agent-based modeling has become vastly used technique in scenarios where autonomous entities interact with each other. This paper examines different marketing behavior and challenges for tenderfoots in online market based on audience and customers. Agent-based modeling is used to develop a simulation model for virtual market. Effect of customers' behavior and advertisements on sellers' ratings and sales volumes is analyzed using NetLogo simulations. Analysis depicts that getting knowledge of different aspects through simulations significantly reduces investment risk in e-commerce market.**

***Index Terms*—ABMS, e-commerce, B2C, virtual market, customer, seller, behavior**

I. Introduction

Since early ages, everyone is dependent on others for their necessities. When there was no currency concept, trade was in form of barter. With passage of time and evolution of our society, currency came into play and a formal trade system was introduced. Anyone having enough money, can visit nearby store of their choice and buy the products. This system prevailed the society for centuries and is still in practice all over the world. However, electronic commerce (e-commerce) has revolutionized the conventional marketing approaches in recent past. After introduction of online payment methods by banking sector, it has become very easy to buy and sell products online from home. In this e-commerce trade system, no one needs to visit the market physically. One can just buy desired products through online stores. It has expanded rigorously in last decade for all sectors. The evolution of e-commerce trade, described by *Statista* [1], has been shown in Figure 1.

There are 44.6 million internet subscribers and 32 million Facebook users in Pakistan according to statistics released by US department of commerce's international trade administration. In local perspective, here in Pakistan, many e-commerce sites such as OLX, $daraz$, $goto$ and many other online shopping sites have dominated the local market. But only 16% of country's population have bank accounts [2]. So most of the brands have introduced Cash On Delivery (COD) payment mode to facilitate the customers that has boosted their trade to much extent.

Initially, when e-commerce was being introduced, agile brands adapting e-commerce won significant competitive advantage. However, with the passage of time and increasing interest in this field, it became very easy for sellers to introduce themselves in e-commerce. Now a days, many plug and play e-commerce website themes are available. It develops a very competitive marketing environment since anyone is able to offer services through internet. So, very sound and intelligent marketing strategies are required to be a prevailing seller in e-market. A newbie must be aware of the parameters and factors affecting the sales in particular field. In order to minimize the risk, they must have an outlook of their entire business strategy before investment. The behavior of participating agents such as customers, traders, intermediaries and services providers and their mutual communication should be well understood. To optimize the profit and minimizing the risk, a newcomer must have some simulation of the targeted market.

Many techniques are used to model complex system such as fractals and chaos theory, network theory, Agent-Based Modeling (ABM) and game theory. However, ABM has become vastly used technique in recent past due to its better sketching of complex scenario [3]. ABM is class of computational models for simulating the actions and interactions of autonomous agents with a view to analyze their effect on a system as a whole. In applying ABM to social processes, people's roles are modeled as agents and their mutual interactions are modeled as interactions between these agents [4]. Applying ABM to

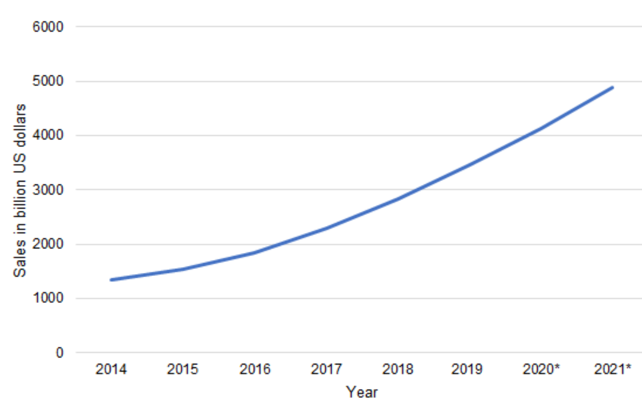

Fig. 1: Worldwide e-commerce sales from 2014 to 2021

e-commerce trade gives better understanding of behavior and causes of behavior in system.

In this paper, an Agent-Based Model and Simulation (ABMS) approach is developed and applied towards e-commerce. The simulation model analyzes the impact of different variables in evaluation of shopping behavior on internet.

II. Literature Survey

E-commerce has briskly evolved in last few years. Before that, researchers paid a lot of attention to understand, model, simulate and analyze the trading in physical markets. Many state-of-the-art techniques such as neural net and ABM [5] based models were also developed and analyzed to improve the existing marketing strategies. An example of such practically used model is the one developed for Procter & Gamble in 2010 [3]. Zhang et al. used ABM to analyze the effect of introducing a new product in marketing as decoy [6].

Rapidly increasing e-commerce trade trend has attracted researchers to divert their attentions to this active field as well. It started from studying impact of key success in e-commerce using regression analysis [7]. Besides neural net models [5], ABM models are also being used to analyze e-commerce marketing. Janssen et al. model was among the first to report as an ABM model to investigate consumer's behavior in virtual market [8].

However, along with buyers and sellers, many other factors are there in the trading process. One of the notable factors is advertisement effect on customers. Okada et al. [9] used ABMS to investigate advertisement impact on consumers' habits and named it as eWOM effect. Such advertisements can be done either through print, broadcast or social media. And almost all e-commerce customers view these ads and are affected by such promotional ads. So, when a seller uses such promotion, they can obviously observe an increasing trend in their sales volume.

Customers of virtual market, however, are not blind to select a seller for purchasing a product. They learn from experience of previous customers of a particular seller just as physical market. It significantly affects the customer's behavior in making choice. CUBES simulator is also ABM based and dedicated to study the customers' interacting behavior and its impact on economic phenomena [10]. Liu et al. [11] used the ABM to study the effect of promotional prices reduction and its impact. Moreover, decision of a customer also depends on its demographic attributes, attitude, perception and beliefs. Technology Acceptance Model (TAM) [12], Theory of Planned Behavior (TPB) [13] and the Theory of Reasoned Action (TRA) [14] have modeled this behavior.

Literature review shows that all the work has been done on single phenomenon especially observing the customer's behavior in market. This paper describes the agent-based modeling and simulation of a virtual market that offers more comprehensive approach to analyze trends in e-commerce with a focus on seller's sales with different social parameters.

III. Research framework

From a top view of an e-commerce market, we can estimate the actors acting in the sale and purchase drama. Main couple of which is seller and a buyer. But the advertisements also play a vital role for sellers in reaching customers. Different sellers use different advertising techniques including print, broadcast and social media to target broad range of audience. The end-to-end process of buying a product in virtual market is affected by a number of factors characterizing both, buyer and seller. All the characteristics of both agents has been shown in Table I and II.

TABLE I: Seller agents characteristics

Label	Definition	Value	Distribution
P_{ij}	Products in cataolg of i^{th} seller	Input variable	Random
Pr_{ij}	Price of j^{th} product in cataolg of i^{th} seller	Input variable	Random
F_i	Popularity of i^{th} seller	Input variable	Random (0-10)
R_i	rating of i^{th} seller	Input variable	Random (0-10)
SV_i	Sales volume of i^{th} seller	Output variable	0 initially

TABLE II: Buyer agents characteristics

Label	Definition	Value	Distribution
A_i	Age fo i^{th} buyer	Input variable	Normally distrbuted
PS_i	Price sensitivity of i^{th} buyer	Input variable	Float-random (0-1)
QS_i	Qaulity sensitivity of i^{th} buyer	Input variable	Float-random (0-1)
I_i	Product being bought by i^{th} buyer	Input variable	Random from set of products

The approach used in this paper is to consider the consumer targeted strategy of sellers. A seller with products appeasing a very small circle of population, will surely need much more time to penetrate in market rather than one who covers as much as possible consumers' interests. Moreover, if we analyze a snapshot of population by age at a time, most of the population consists of age group ranging from 15-35 years. And most internet users come from the same age group thus making the higher tendency of youth to buy products through e-commerce. It deduces that a brand selling youth targeted products can earn much more than the one targeting the oldies. Furthermore, customer reach is also affected by many more factors. In this paper, we present the effect of these factors on the sales of a seller.

A. Simulation model development

The model presented in this paper, as described earlier, based on two agents such as buyers and sellers. According to Pakistan Bureau of Statistics (PBS), most of our population consists of youth (age group of 15-34 years) [15]. And the statistics of internet users provided by *Statista*, most of the buyers of e-commerce sites come from an age group of 18-35 years [16]. So, in our model, we have modeled the buyer's population as normal distribution. However, only the adult and older citizens (18+) are considered as customers in market. A buyer is classified as either young, mature or an old man. Everyone who comes to buy a product, has a certain level of price and quality sensitivity. Each seller can sell any number of products targeting any subset of the buyer's categories. Two sellers can sell same product with different price tags. In this case, the buyer will choose the better product based on their taste such as price and quality sensitivity. The quality measure of a seller is based on the ratings by previous customers buying the same product.

Overall flow of simulation model is shown in Figure 2.

B. Agent interactions and rules of behavior

In the first phase, the simulation model creates the buyer's populations based on population pyramid theory. Most of the population consists of young people and like to buy certain products. While mature people are lesser in number and tend towards some different products. The third category is of senior citizens who have their own choices in market. On the same hand, seller's population is also generated. Each seller can sell any set of products such as targeting youth, mature, oldies or any subset of this set. Everyone can set its own demand for each product irrespective of the demands of other brands. Initially no brand uses advertisements, however the advertisements can be generated during simulation.

Each buyer wants to buy a certain product at a time. It searches on internet and finds the most popular brand with required product in catalog. Then based on its sensitivity parameters, it checks if the seller is in accordance with its criteria. For example, in case of price, criteria are met if demanding price is equal to or less than the expected price. Parameter expected price is difficult to estimate. So, the expected price is modeled as the price of product demanding by a seller at index I in sorted sellers list where i is given by $i = x - x * +p + 1$ where p is the price sensitivity of the customer.

Similarly, in case of quality sensitivity, the expected rating of a seller is the rating of the seller at index i in a sorted list of sellers. If a seller satisfies both the criteria, buyer successfully buys the product from this seller and its popularity is increased based on this sale. However, this popularity doesn't mean its rating. Each buyer rates its seller afterwards as either -1,0 or +1 based on bad, normal or good experience. The overall rating of a seller is used as quality standard measure of the seller for upcoming customers.

IV. Simulation setup and results

The developed simulation model in section III-A has been implemented in NetLogo software [17]. NetLogo is a multiagent programmable modeling and simulation environment. The flow of simulation set up for our model has been pseudo coded in algorithm 1. The flow describes the behavior of model for a single buyer purchasing a product in a single tick. The process is done for each buyer in parallel in each tick.

For analyzing the model, we generated a set of products for each age group, buyers and seller population. Products are

Algorithm 1: Simulation flow in NetLogo

Generate normally distributed $buyers$ population buying product $'x'$;
Generate sets of $products$ for young, mature and old people;
Generate $sellers$ population selling a sub set of products;
while $i < length(sellers)$ **do**
  if i^{th} *seller sells product x* **then**
    Add i^{th} seller to List SL
  end
end
sort SL based on its F_i score;
while $j < length(SL)$ **do**
  if $PS_b > QS_b$ **then**

$$ind = length(SL) - length(SL) * PS_b + 1 \tag{1}$$

    $SSL1 = subList(0, ind, SL)$;
    if $seller_j$ *is member of SSL1* **then**

$$ind = length(SSL1) - length(SSL1) * QS_b + 1 \tag{2}$$

      $SSL2 = subList(0, ind, SSL1)$;
      if $seller_j$ *is member of SSL2* **then**
        $Buyer_b$ buys from a random seller from SSL2;
        SV_j++
      else
        exit;
        `// Unhappy buyer doesn't buy anything`
      end
    else
      $F_j - -$;
    end
  else

$$ind = length(SL) - length(SL) * QS_b + 1 \tag{3}$$

    $SSL1 = subList(0, ind, SL)$;
    if $seller_j$ *is member of SSL1* **then**

$$ind = length(SSL1) - length(SSL1) * PS_b + 1 \tag{4}$$

      $SSL2 = subList(0, ind, SSL1)$;
      if $seller_j$ *is member of SSL2* **then**
        $Buyer_b$ buys from a random seller from SSL2;
        SV_j++;
      else
        exit;
      end
    else
      $F_j - -$;
    end
  end
end
cR=$Buyer_b$ rates its seller randomly as -1,0 or +1;
R_{seller}=$R_{seller} + cR$;

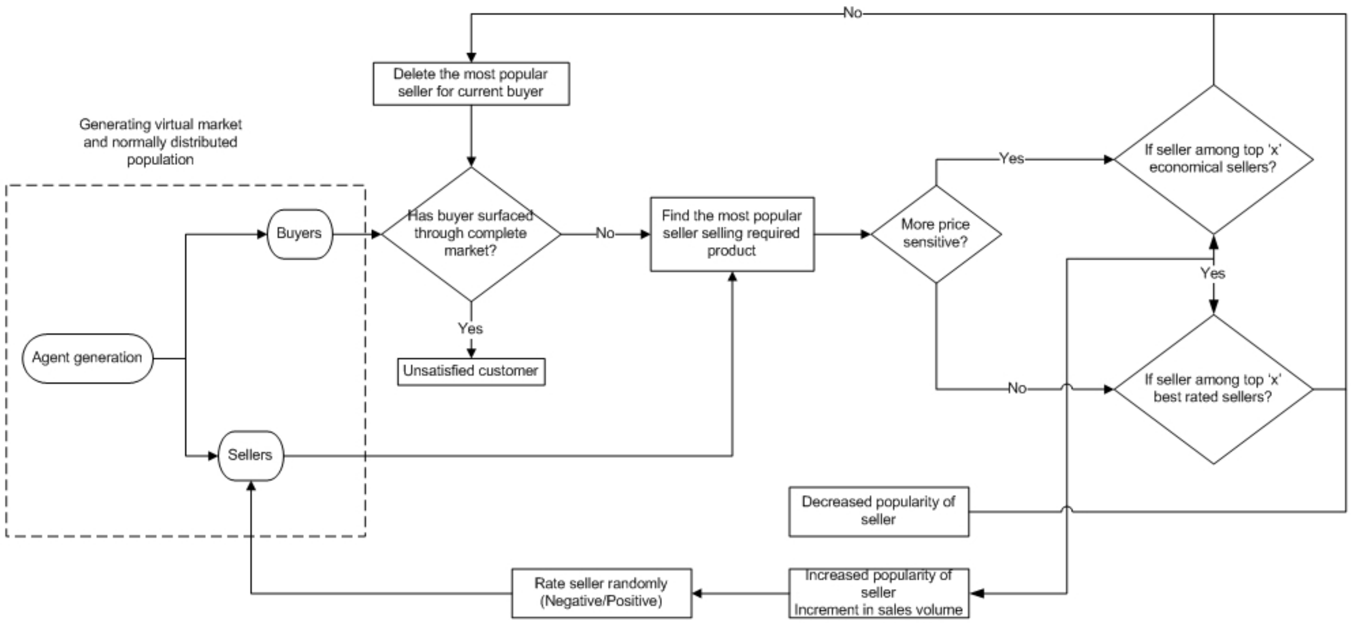

Fig. 2: Flow of simulation model

named as alphabets A to K representing different products for different age group. Buyers population has youth as its largest population fraction. And all the buyers are initiated with random price and quality sensitivity measure. A total of 5 brands are available in market targeting different audience. A different comparisons of these sellers have been described in analysis sections.

TABLE III: Age categorised selling products in simulation of virtual market

Category	Products
Youth	list("A","B","C","D","E","F")
Mature	list("G","H","I")
Old	list("J","K")

A. *Effect of population fraction*

In first phase of our simulation, we checked the effect of largest population fraction on a seller's sales volume. Sellers attribute for this particular phase are given in Table IV.

TABLE IV: Generated sellers for section IV-A

Seller	Sellings products
Seller 0	All
Seller 1	Only youth's
Seller 2	Overlapped set of mature and old
Seller 3	Only mature's
Seller 4	Only olds'

From Figure 3, we can conclude that the seller targeting the largest population fraction can earn much more as compare to others. Though seller 1 is not targeting all age groups even then it has much large sales volume that is actually due to its targeted audience. It is selling youth products who is the largest constituent of population. Due to which, its sales are much more than that of seller 2, 3 and 4 who are targeting mature and old people.

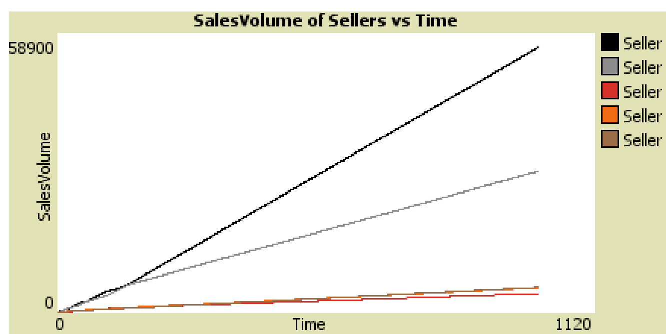

Fig. 3: Effect of population groups on e-commerce sales

B. *Effect of advertisements*

As discussed earlier, advertisements play an important role in reaching to customers. A seller with more advertisements on public platforms goes more popular than its competitors. In our simulation model, this phenomena are handled by a seller's characteristics F_i in Algorithm 1. A seller's F_i score is measure of its popularity and increases with its increasing ads. Keeping the same seller's configuration generated in last section, we can observer the commercials' effect in Figure 4.

Sales of seller 0 were less than that of seller 1 in spite of its largest targeted audience. It is due to fact that the all age groups will also go for seller 2, 3 and 4 based on their price and quality sensitivity. So, in case if all buyers tend to buy products from their specific sellers, then seller 0 sales will be reduced. However, he uses advertisements in this scenario. As soon as seller 0 starts advertising its products, its sales go more than that of seller 1.

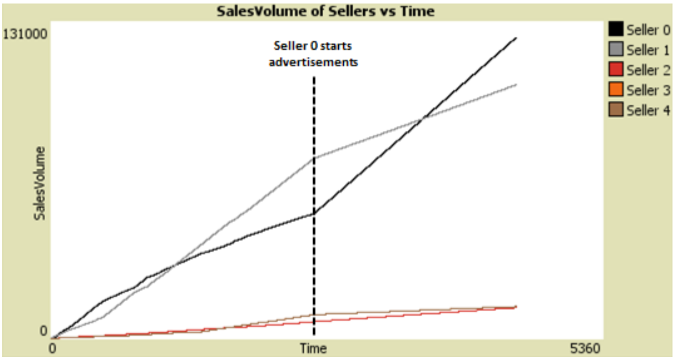

Fig. 4: Effect of advertisements on e-commerce sales

C. Effect of competition

On the other hand, if all the sellers sell the product of same age group then they have to face a lot of competition and sales volume of each seller will be less deviated from mean. To observe this effect, we change all sellers targeted audience to youth expect seller 4 (to avoid simulation error for mature and old population). It is obvious from Figure 5, sales of all sellers from 0 to 4 are less deviated from mean. Sales volume of seller 0 and 1 is reduced while that of seller 2 and 3 has been increased. Whereas seller 4 is now only brand selling products of old and mature population and, hence enjoying largest sales volume. It is due to the fact that the targeted audience of seller 4 is now larger than the individual targeted audience of all rest of the sellers.

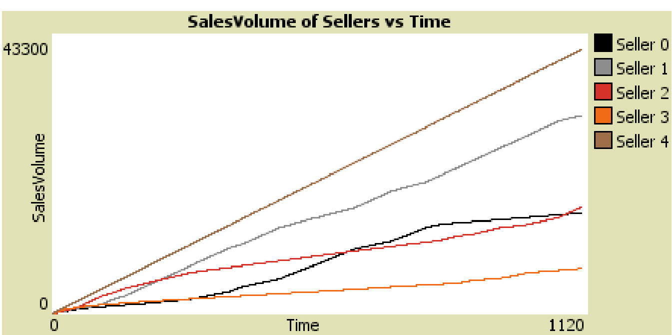

Fig. 5: Effect of competition on seller's sales

D. Challenges for a new brand

In the scenario given in Table IV, what will happen if a new brand wants to introduce itself in market? To observe this, we introduce a new seller (named NewSeller) during running simulation. The new seller is also a targeting only youth age group. From simulation results in Figure 6, it can be seen that though the sales volume of newbie goes more than seller 2, 3 and 4 but it can't earn more than its competitors in market. However, it may defeat seller 0 and 1 as well with coming into market earlier or using much more advertisements (effect described in Section IV-B).

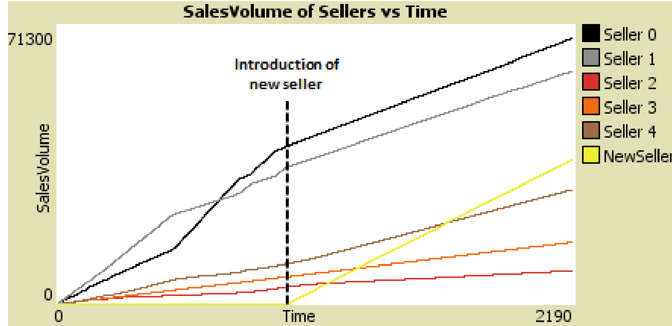

Fig. 6: Effect of a new brand in markets' sales

E. Effect of rating on sales

Each buyer rates its seller randomly as -1,0 or +1 after buying a product. The overall rating of a seller is used as its quality standard for upcoming quality sensitive buyers. In Figure 7 at point A, the rating of seller 0 starts falling and that of seller 1 starts elevating. However, rating from a single buyer can't judge quality of a seller's products. However continuous negative rating means the seller is actually of bad standard and hence its sales fall below than seller 1 at point B. This is exactly in accordance with actual phenomena in physical market.

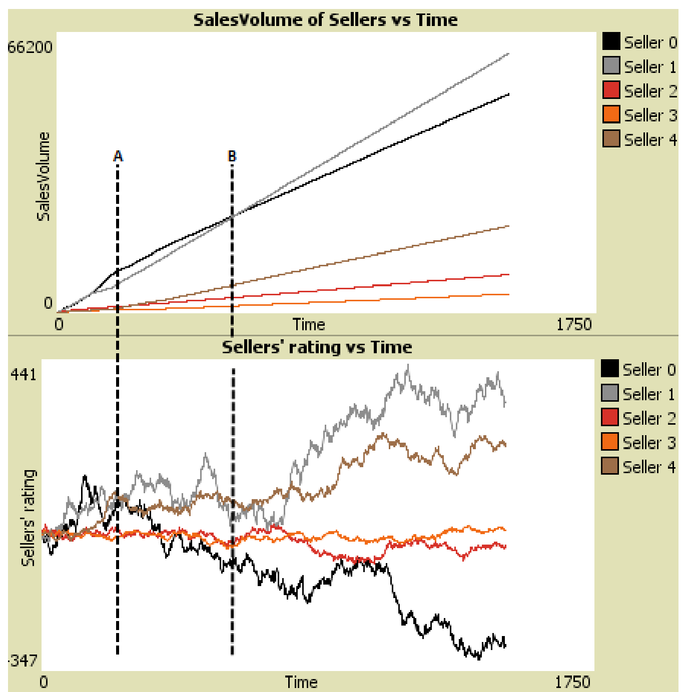

Fig. 7: Effect of rating on seller's sales

V. Discussion

The simulation results, visualized from last section, show that the sales of brands targeting the largest community of population will enjoy more profit than the other sellers. Advertisements through different platforms help a seller to reach maximum people. And the profit of a seller is directly proportional to the number of people a brand reaches. With increasing number of brands targeting same audience, profit of all brands is distributed with less deviation around mean. It is due to the fact that a population is price and quality sensitive randomly. So, some go for cheaper sellers and some for quality sellers. And eventually every brand gets customers and earnings of all brands are less deviated. If a new brand wants to penetrate into the market, it'll has less earnings than its competitors unless it'll advertise more than those. Moreover, a brand's sales are dependent upon the ratings done by its older customers. Positive feedback from customers help a seller to be a reputable brand and, hence enjoying more earnings.

The results achieved in this paper are based on a naive model. Model takes price and quality as input parameters. However, the model can be made more accurate if both of input parameters are modeled as function of buyers' personal and demographics qualities such as age, income, country and living standards. Moreover, a buyer's sensitivity towards advertisements is also not modeled here assuming that ads influence all the population equally. However, this is not the case in actual and buyer's sensitivity should also be modeled.

VI. Conclusion

With evolution of e-commerce, sellers' competition has been increasing rapidly in virtual market. This demands pre-planning for brands intending to penetrate in it. A very well formulated and planned marketing strategies are the need of hour to well compete the existing brands. This paper addresses the analysis of sales volume of sellers in virtual market interacting with different type of consumers. The actors acting in e-commerce trade are modeled using agent-based simulation model. Buyer's population, normally distributed based on age, buy the products of their interest from any seller. Sales volumes of different sellers have been analyzed in different scenarios with different populations through developed model.

References

[1] "Retail e-commerce sales worldwide from 2014 to 2021," https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales, 2018, accessed: 2018-12-09.

[2] U. D. of Commerce's International Trade Administration, "Pakistan - ecommerce," https://www.export.gov/article?id=Pakistan-eCommerce, 2018, accessed: 2018-12-09.

[3] C. M. Macal and M. J. North, "Tutorial on agent-based modelling and simulation," *Journal of Simulation*, vol. 4, no. 3, pp. 151–162, 2010.

[4] N. Gilbert and K. G. Troitzsch, *Simulation for the Social Scientist*. Milton Keynes, UK, USA: Open University Press, 2005.

[5] R. Riedl, M. Hubert, and P. Kenning, "Are there neural gender differences in online trust? an fmri study on the perceived trustworthiness of ebay offers," *MIS Quarterly*, vol. 34, no. 2, pp. 397–428, 2010.

[6] T. Zhang and D. Zhang, "Agent-based simulation of consumer purchase decision-making and the decoy effect," *Journal of Business Research*, vol. 60, no. 8, pp. 912 – 922, 2007, complexities in Markets Special Issue.

[7] D. J. Kim, D. L. Ferrin, and H. R. Rao, "A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents," *Decision Support Systems*, vol. 44, no. 2, pp. 544 – 564, 2008.

[8] M. A. Janssen and W. Jager, "An Integrated Approach to Simulating Behavioural Processes: a Case Study of the Lock-in of Consumption Patterns," *Journal of Artificial Societies and Social Simulation*, vol. 2, no. 2, pp. 1–2, 1999.

[9] I. Okada and H. Yamamoto, "Effect of online word-of-mouth communication on buying behavior in agent-based simulation," in *6th Conference of the European Social Simulation Association*, 2009.

[10] L. Ben Said, A. Drogoul, and T. Bouron, "Multi-agent based simulation of consumer behaviour: Towards a new marketing approach," *Proceedings of the International Congress on Modelling and Simulation (MODSIM 2001), Canberra, Australia*, 01 2001.

[11] X. Liu, Z. Tang, J. Yu, and N. Lu, "An agent based model for simulation of price war in b2c online retailers," *INTERNATIONAL JOURNAL ON Advances in Information Sciences and Service Sciences*, vol. 5, pp. 1193–1202, 03 2013.

[12] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User acceptance of computer technology: A comparison of two theoretical models," *Management Science*, vol. 35, no. 8, pp. 982–1003, 1989.

[13] I. Ajzen and M. Fishbein, *Understanding attitudes and predicting social behavior*. Prentice-Hall, 1980.

[14] I. Ajzen, *From Intentions to Actions: A Theory of Planned Behavior*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1985, pp. 11–39.

[15] P. B. of Statistics, "Population by 5 year age groups - pakistan," http://www.pbs.gov.pk/sites/default/files/tables/POPULATION%20BY\%205%20YEAR%20AGE%20GROUPS%20-%20PAKISTAN.pdf, 2018, accessed: 2018-12-09.

[16] "Leading product categories bought online among internet users in the united states as of november 2017, by age group," https://www.statista.com/statistics/693629/usa-online-shopping-product-categories-by-age, 2017, accessed: 2018-12-09.

[17] U. Wilensky, "Netlogo," http://ccl.northwestern.edu/netlogo/, 1999, accessed: 2018-12-09.