A Simulation Model using Transaction Cost Economics to Analyze the Impact of Social Media on Online Shopping

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Abstract. In this paper, we have developed an agent-based simulation model to study the influence of social media on consumers' inclination towards on-line shopping. Social media includes web-based and mobile based technologies which are used to turn communication into interactive dialogue between organizations, communities, and individuals. Building upon the Transaction Cost Economics theory, the objective of our study is to examine the effect of social media on the "perceived transaction cost" of an individual, which determines his/her inclination to buy online. Transaction cost economics (TCE) theoretically explains why a transaction subject favors a particular form of transaction over others. Since purchasing from online stores can be considered a choice between the internet and traditional stores, it is reasonable to assume that consumers will go with the channel that has the lower transaction cost. Using agent-based models, we have studied the rate of adoption of on-line shopping by consumers.

Keywords: Transaction Cost, Social Network, Online shopping, Consumer Behavior

1 Introduction

Since the advent of the internet, online shopping has progressively been gaining primacy throughout the world, drastically altering the established structure of markets [1,2,3]. This ascent of online stores is taking a toll on traditional markets. Amazon, one of the most successful online firms, is currently valued at over $79 billion, which is 40 percent higher than the combined value of two large and successful offline retailers, Target and Kohl's, who have 2800 stores between them. Barnes & Noble, while still large, has also seen diminish of its market share [4].

Consumers interact, through processes such as imitation and conditioning, by means of individuals and groups of individuals (friends, family, etc.), which comprise the "social contacts" of the consumer [5, 6]. These contacts, according to their cohesion degree, influence more or less the consumer's purchase behavior. The online social network, which is a direct consequence of the same technological boom of the 90s that brought about the dominance of e-commerce, has revolutionized the way consumers interact with and influence each other. These interactions tend to change the "*transaction cost*" individuals associate with online shopping. A transaction cost is a cost incurred in making an economic exchange, i.e, it is the cost of participating in a market [7]. Transaction cost economics (TCE) is most commonly associated with the work of Oliver Williamson [8, 9, 10]. Using this transaction cost economics perspective, Teo, et al. [11] presents an empirical study for understanding consumers' on-line buying behavior. The results indicate that consumers' willingness to buy online is negatively associated with their perceived transaction cost.

In this paper, our objective is to demonstrate the adoption process of a consumer with regard to on-line shopping using an agent-based simulation model. We have studied the interaction among three entities to model this phenomenon: (i) Online Stores ($STORE_{online)}$ (ii) online consumers ($CONSUMER_{Online)}$ and (iii) brick-and-mortar consumers who may be influenced into shopping online ($CONSUMER_{B\&M)}$

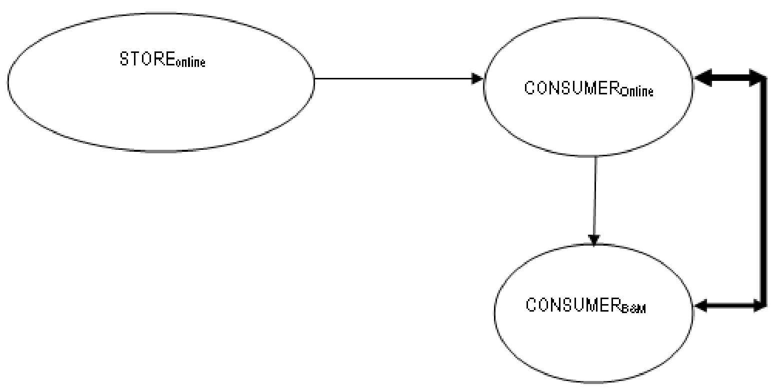

Fig. 1. An Interaction Model illustrating the adoption process

The influencing patterns between entities are illustrated below:

- ✓ $CONSUMER_{Online}$ influences $CONSUMER_{B\&M}$ to move towards online shopping using online social networks. Thus, more consumers become online consumers (early majority); As this happens, these consumers in turn influence traditional consumers in their social circle, eventually turning them into online consumers (late majority).
- ✓ On some occasions online stores ($STORE_{online}$) may generate negative impacts through unacceptable service quality (delayed delivery, unacceptable product quality, etc) that may force some consumers in $CONSUMER_{Online}$ to go back to B&M shopping methods.

We will show how a consumer's perceived transaction cost is influenced through these interactions. Transaction cost economics (TCE) theoretically explains why a transaction subject favors a particular form of transaction over others. Since purchasing from online stores can be considered a choice between the internet and traditional stores, it is reasonable to assume that consumers will go with the channel that has the lower transaction cost. In this context, we study how online social networks accelerate this adoption process by constantly altering the transaction costs attached with online shopping, as perceived by individuals. The transition between $CONSUMER_{B\&M,}$ to $CONSUMER_{Online}$ is covered in a considerably shorter period of time than it would have been in the absence of the social media.

To study these effects, agent-based simulation model is an invaluable tool [12]. Agent-based modeling is a bottom-up approach to understanding and analyzing complex, non-linear markets [13]. The method involves creating artificial agents designed to mimic the attributes and behaviors of their real-world counterparts. Using such a model, we may incorporate factors of social influence, heterogeneity, erratic rationality and in general present a fairly realistic picture of the consequences of inter-agent interaction. Agent-based simulations [14, 15] have offered during the last decade an interesting methodological issue and an innovative tool for specifying and validating behavioral individual models that are believed to be at the origin of emergent social and organizational phenomena. Using agent-based models, we create virtual populations including several hundreds of artificial consumers to study the rate of adoption of on-line shopping behavior by consumers.

2 A Transaction Cost Based Model

Transaction cost economics (TCE) theoretically explains why a transaction subject favors a particular form of transaction over others. The basic principle of TCE is that people like to conduct transactions in the most economic way. Since purchasing from online stores can be considered as a choice between the internet and traditional stores, it is reasonable to assume that consumers will go with the channel that has the lower transaction cost. Therefore, TCE becomes a viable theory for explaining the internet shopping decision of consumers. Specifically, whether a consumer would buy a product through the Internet is determined by the perceived transaction cost of the consumer [11]. Using this transaction cost economics perspective, Teo, et al. [11] shows that consumers' willingness to buy online is negatively associated with their perceived transaction cost.

Each consumer assigns a perceived transaction cost T to online shopping based on a set of factors like product uncertainty, convenience, economic utility, etc. The performance uncertainty of products bought online is one of the consumers' major concerns [11]. Thus, consumers' initial perception about high product uncertainty in online shopping increases perceived transaction cost. Online buying, as an alternative to physical shopping, offers more convenience to consumers because they can save time and effort in searching for product information. Therefore, consumers perceive that convenience is high in on-line shopping and therefore perceived transaction cost is low in this respect. Also, the consumers perceive that economic utility is high in on-line shopping thus making perceived transaction cost low in this respect. Based on these factors, a consumer assigns an overall perceived transaction cost T to online shopping. The social interactions of a consumer will influence the values of T. A consumer becomes a $CONSUMER_{Online}$, once perceived transaction cost goes below a certain threshold value T^H.

Process of Influence and Adoption

Positive Influence: The adoption process is initiated when a consumer X, belonging to $CONSUMER_{Online}$, interacts with his/her friends within his/her social network framework. This process of interaction will influence another consumer Y, (who belongs to $CONSUMER_{B\&M}$ and is a friend of X,) to alter his/her transaction cost. The nature of this interaction between the two is illustrated as follows:

Let T(Y) is Y's perception of Transaction costs associated with online shopping. Let us also assume that S is the commodity factor ($0<S<1$) that depends on the nature of the commodity /market we consider e.g. shoes/apparel/books /air-ticketing and so on. S is closer to 1 when the commodity does not require any look-and-feel type inspection and service is guaranteed (e.g. book, air-ticket, etc). S is closer to 0, when the commodity requires a look-and-feel type inspection and service is uncertain (e.g. shoes, apparel, etc.)

After influence, each component of Y's transaction cost will be reduced as follows:

$$T(Y_{new}) = T(Y) - S^* T(Y)$$

So, when S is closer to 1, transaction cost of *Y* will reduce faster. Once T(Y) < [threshold T^H], Y "crosses over" to become a member of the $CONSUMER_{Online}$ community. Gradually, the number of members in $CONSUMER_{Online}$ rises in the population.

Negative Influence: As indicated earlier, members belonging to the $CONSUMER_{Online}$ community have a perceived transaction cost below the threshold T^H that makes them inclined towards online shopping. However, this is not a static scenario. As indicated in figure 1, some on-line consumers may also experience negative influences from some on-line stores (delayed delivery, unacceptable product quality, etc) that may force them to go back to B&M shopping

Let us assume that any consumer X belongs to $CONSUMER_{Online}$ community and let us assume that T(X) = X's perception of Transaction cost associated with online shopping. Let us also assume that F is the negative Impact Factor s that depends on the nature of impact of the negative influence of $STORE_{Online}$ on X. After randomized influence (with a probability P) of $STORE_{Online}$ as stated above, X's transaction cost will be increased as follows:

$$T(X_{new}) = T(X) + F * T(X)$$

For example, let us assume that X has received a product of unacceptable quality through on-line shopping and X associates an impact factor F = 0.5 for this event. So, X's perceived transaction cost associated with online shopping (T(X)) will change as: $T(X_{new}) = T(X) + 0.5 * T(X)$. If this happens multiple times, T(X) will eventually be greater than [threshold T^H] and X "crosses over" to become a member of $CONSUMER_{B\&M}$ community.

3 Agent Based Modeling And Simulation

Agent-based modeling and simulation (ABMS) is a new approach to modeling systems comprised of interacting autonomous agents [16]. Agents are autonomous decision-making entities or self-directed objects. Agent-based models are made up of agents and a framework for agent interactions. Agent-based modeling allows the behavior of system components (i.e., the agents) to be used to forecast the behavior of the overall system [17].

Economics is experiencing a paradigm shift in response to agent-based modeling. The field of Agent-based Computational Economics (ACE) has grown up around the application of ABMS to economic systems [12]. Some of the classical assumptions of micro-economic theory are: (1) Economic agents are rational; and, (2) Agents are homogeneous, having identical characteristics and rules of behavior. These assumptions are relaxed in ABMS applications to economic systems. Behavioral economics is a relatively new field that incorporates experimental findings on psychology and cognitive aspects of agent decision making to determine people's actual economic and decision making behavior. Thus, agent-modeling is a promising basis for modeling social life as interactions among adaptive agents who influence one another in response to the influences they receive [6].

The Simulation Framework

Using agent-based models, our goal is to create virtual population of interacting Consumers and Stores to study the rate of adoption of on-line shopping by consumers. A variable transaction cost $T(n)_{TOTAL}$ is associated with each consumer n, which indicates his/her perception of the transaction cost associated with on-line shopping. When $T(n)_{TOTAL} < T^H$ (where T^H is the threshold transaction cost), the consumer will decide to purchase on-line.

Initially, there is a set of consumers $\in CONSUMER_{Online}$ with $T(n)_{TOTAL} < T^H$. They are the *early adoptors* of on-line shopping. During the course of interaction, they reduce the transaction cost of consumers $\in CONSUMER_{B\&M}$, as described in section 2.3. As a direct consequence of this, a consumer $\in CONSUMER_{B\&M}$ is now classified under $CONSUMER_{Online}$. Gradually, the number of $CONSUMER_{Online}$ rises in the population. However, some on-line consumers may also experience negative influences from some on-line stores that will increase their perceived transaction cost towards online shopping and may force them back to B&M shopping methods (depending on the value of the resultant transaction cost). The agent based simulation model that we develop will demonstrate the gradual changes in perceived transaction cost of an individual towards online shopping and will help us study this back and forth movement between $\text{CONSUMERS}_{\text{online}}$ and $\text{CONSUMERS}_{\text{B\&M}}$ and its dependence on a set of specified parameters.

The proposed scheme is evaluated on a simulated social network environment under a variety of conditions to estimate the rate of adoption (of on-line shopping) against time. We present simulations for networks with 1000 and 10000 artificial consumers (the agents). Each consumer has an average number of friends N_n which is a variable simulation parameter. Also, we vary the initial number of online consumers (*Early Adopters)* who will act as *influencers* in the system. The adoption process is initiated when an agent $\in \text{CONSUMER}_{\text{Online}}$ interacts with its friends in the network. This process of interaction will influence an *agent* $\in \text{CONSUMER}_{\text{B\&M}}$ (provided they are friends) to reduce its total transaction cost in favor of on-line shopping, as depicted in section 2.3.

These results are, of course, indicative and not validated by empirical studies. To demonstrate the usability of the model, we have generated T values randomly. For an initial set of agents $\in \text{CONSUMER}_{\text{Online}}$, the random values are chosen in such a fashion that T for each is less than the threshold T^H (=10). For $\text{CONSUMER}_{\text{Online}}$ we choose random values between 1 to 10, while for $\text{CONSUMER}_{\text{B\&M}}$, random values between 11 to 50(>10) are chosen.

We have studied the growth in number of online consumers against time as a function of following six parameters:

- Population Size participating in given social network environment (i.e total number of consumers under consideration, **N**)
- Average number of friends $\mathbf{N_n}$ per consumer
- Number of Early Adopters (i.e. initial number of online consumers), **I**, in given social network
- Commodity factor, **S** (0 <S<1) [section III.A.]
- Impact Factors **F** denoting magnitude of negative impact of $\text{STORE}_{\text{Online}}$ on $\text{CONSUMER}_{\text{Online}}$ (figure 1),
- Probability **P** of impact mentioned above. For example, P=0.05 means that for every 100 transactions, online stores create 5 negative impacts on online consumers with impact factor F.

4 Results and Discussions

4.1 Effect of N_n on Growth-Rate of Online Consumers

Figure 2 shows the growth-rate of online consumers against time with I=10 and average number of friends per consumer, i.e. N_n = 10, 50 and 100 respectively, where Impact Factors **F**=1.0 and Probability **P** of negative impact =0.04. The growth in number of online consumers depends on number of friends N_n per consumer. The growth saturates at 700 (70% of total population) at N_n = 5. This means that, under the given circumstance, the negative influence of $STORE_{Online}$ on consumers will hold back dynamically 30% consumers (300 out of 1000 on the average) towards B&M shopping, when N_n =5. The fluctuating portion of the graph (between label B and C in figure 3) indicates dynamic transitions of consumers from $CONSUMER_{On-line}$ to $CONSUMER_{B\&M}$, and vice versa, as shown and explained in figure 1.

But, as the number of friends per consumers increases to 10 and 15, the saturation point shifted up at 85 to 90%, (figure 2), indicating that stronger the influence of social network (more the number of friends), more will be the inclination towards online shopping.

Also, the growth-rate in figure 2 becomes sharper with increase in number of friends. Similarly, the starting point of the adoption process (point A in the graph) also decreases with increase in N_n, since a larger number of friends increases the probability of much faster adoption. For the same reason, positive influence of a large number of friends offsets the negative impact of online stores on consumers. As a result, the saturation point depends on the number of friends. However, the negative influence of $STORE_{Online}$ on consumers will always hold back dynamically a certain % of consumers towards B&M shopping.

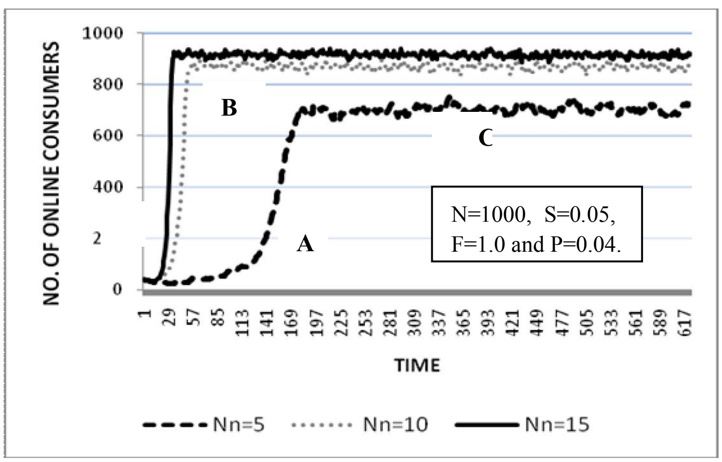

Fig 2. Growth-rate of online consumers with I=10 at different N_n

4.2 Effect of F on Growth-rate of Online Consumers

Negative Impact factor F and probability of negative impact P are responsible for increasing the transaction cost of an online consumer with respect to online shopping and consequently, pushing him/her back to B&M shopping method (when transaction cost > T^H). Fig 3 analyses the effect of F at P=0.04. As expected, when the negative impact factor of $STORE_{Online}$ is high (3.0), the number of consumers fluctuating between $CONSUMER_{Online}$ and $CONSUMER_{B\&M}$, and vice versa is quite high and both the growth-rate and saturation point are quite low (40%) compared to those at F=1.0 (where saturation point is at 70%).

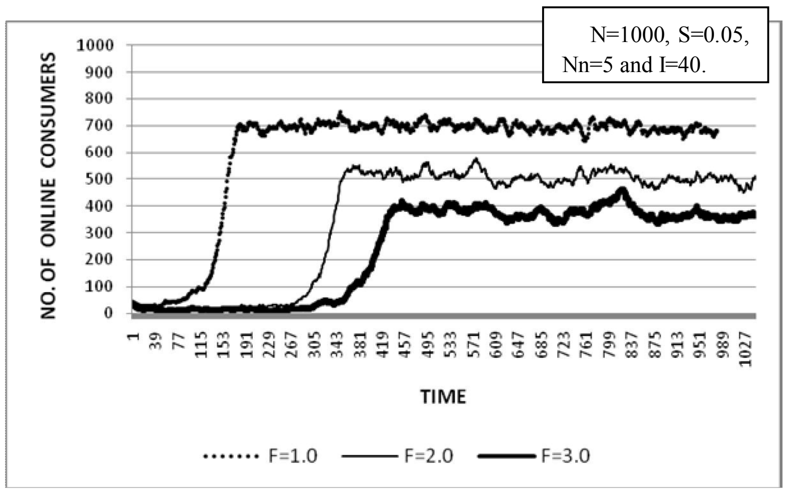

Fig 3. Growth-rate of online consumers with P=0.04 at different F

4.3. Effect of P on Growth-rate of Online Consumers

As indicated earlier**,** on-line consumers may experience negative impact from some on-line stores (delayed delivery, unacceptable product quality, etc) that may force them to go back to B&M shopping methods. P is the probability of such an impact. For example, P=0.05 signifies that online consumers suffer a negative impact once every 20 transactions. Fig. 4 depicts the effect of P at F=1.0. As expected, lower the probability of negative impact, higher will be the number of consumers inducted towards online shopping. So, at P=0.01, saturation level i.e. number of online consumers is almost 90% of the total population.

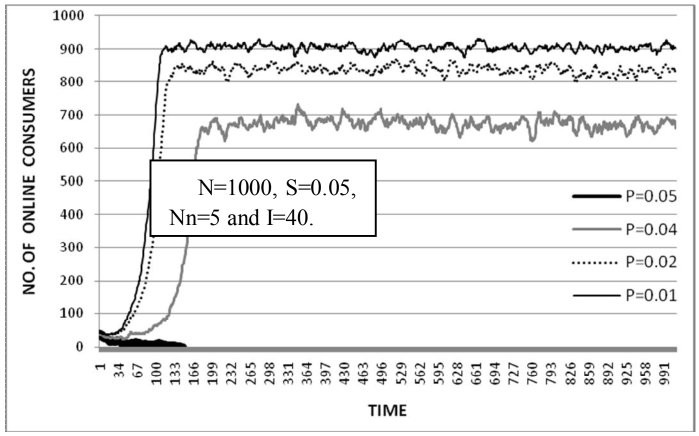

Fig 4. Growth-rate of online consumers with F=1.0 at different P

However, in the given situation, it is very interesting to note that if P=0.05 or higher, the entire population will move towards B&M shopping. Even the early adopters will not be able to tolerate the increased frequency of negative impacts (more than once in every 25 transactions) and they will become B&M shoppers.

4.4 Effect of N on the growth rate of online consumers

In order to test the scalability of our model, we have fixed all other parameters except N. Figure 5 shows the growth-rate of online consumers against time with N=1000, 3000, 5000 and 10000, where Nn=5, I=0.4%, , S=0.05, P=0.04 and F=1.0

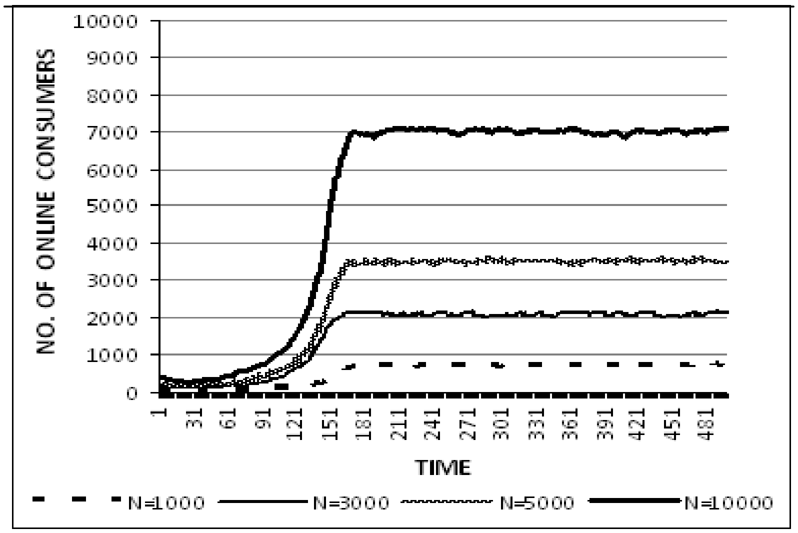

Fig 5. Growth-rate of online consumers at different N

As shown, the *growth in number of online consumers does not depend on N*; it saturates at 70% of total population in all cases under the given circumstances. Hence, in the given scenario, the negative influence of $STORE_{Online}$ on consumers will always hold back dynamically 30% consumers on the average towards B&M shopping and it is independent of total number of consumers N.

4.5 Discussions

From the above observations, the following conclusions can be deduced:

- ✓ Social media accelerates online shopping adoption by constantly altering the transaction costs individuals associate with it. The transition between the "early adopters" (of online shopping) and the "early majority" is covered in a considerably shorter period of time than it would have been in the absence of the social networking effect. This is evident from fig 2 where the growth-rate becomes sharper with increase in number of friends and on-line social media is instrumental in increasing the average number of friends per consumer.
- ✓ However, the long-term success of online stores depends on their sustained

performance. With increase in the growing popularity of online shopping, their service will suffer. So they will have to keep up with the growing popularity, otherwise their negative impact with take a heavy toll on their success making their success short lived. If they commit mistakes or fail to give sufficient attention to customers' needs, the negative Impact factor F and probability of negative impact P of online stores will increase the transaction cost of existing online consumers with respect to online shopping and consequently, will push them back to B&M shopping, as shown in fig.3 and fig. 4. Consumer interactions using social media will propagate this negative impact much faster than it would have been without the presence of social media.

5 Conclusion

Several researchers have predicted the gradual growth in shares of online retailers to be linear [18]. However, those analyses have not considered the impact of on-line social networks, which is exerting a heavy influence on consumer purchase behavior and diffusion (from offline to online). Most on-line retailers are endeavoring to tie-up consumers' shopping activities with their presence in social networks (such as Facebook or Twitter). Thus, neutral consumers are quickly getting influenced in favor of shopping online. Hence, the predicted growth rate is exponential, and not linear. Brick-and-mortar firms, i.e conventional retailers must thus pursue a strategy of omnichannel retailing—an integrated approach that combines the advantages of physical stores with the experience of online shopping [18]. Only then can they survive the paradigm shift we have exemplified here.

References

1. Smith, M.D., Bailey, J. and Brynjolfsson, E. (1999). "Understanding digital markets: review and assessment', in E. Brynjolfsson and B. Kahin (Eds.) *Understanding the Digital Economy: Data, Tools and Research,* MIT Press, Cambridge, Mass,USA.
2. Wigand, R.T. (1997). "Electronic commerce: definition, theory, and context", *The Information Society*, Vol. 13, pp.1–16.
3. [Wang, Zhu (2007). "Technological Innovation and Market Turbulence: The Dot-Com Experience." *Review of Economic Dynamics*, 10(1), 2007
4. Lieber, Ethan and Chad Syverson (2011). "Online vs. Offline Competition", Prepared for the Oxford Handbook of the Digital Economy, January, 2011.
5. Zielinski J., T. S. Robertson and S.Ward (1984). "Consumer behavior", *Scott Foresman series inmarketing,* 1984
6. Antonides G.(1989). "An attempt at integration of economic and psychological theories of consumption", *Journal of Economic Psychology,* 10(1), pp.77-99, 1989
7. Rindfleisch, A. and Heide, J.B. (1997). "Transaction cost analysis: past, present and future applications", *Journal of Marketing*, Vol. 61.

8. Williamson, O.E. (1979). “Transaction cost economics: the governance of contractual relations”, *Journal of Law and Economics*, Vol. 22.
9. Williamson, O.E. (1981). “The economics of organization: the transaction cost approach’, *American Journal of Sociology*, Vol. 87.
10. Williamson, O.E. (1985). “*The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting”,* The Free Press, New York.
11. Teo, T.S.H., Wang, P. and Leong, H.C. (2004) ‘Understanding online shopping behaviour using a transaction cost economics approach’, *Int. J. Internet Marketing and Advertising*, Vol. 1, No. 1.
12. Tesfatsion, L. (2005). “Agent-based Computational Economics (ACE)” www.econ.iastate.edu/tesfatsi/ace.htm
13. Twomey Paul and Richard Cadman (2002). “Agent-based modeling of customer behavior in the telecoms and media markets”, Info 4,1, 2002.
14. Ben Said,L., A. Drogoul and T. Bouron (2001). “Multi-Agent Based Simulation of Consumer Behaviour: Towards a New Marketing Approach”, In Ghassemi, F., Post, D.A., Sivapalan, M. and Vertessy, R. (eds) MODSIM 2001 International Congress on Modelling and Simulation. Volume 1, pp. 71-76. Modelling and Simulation Society of Australia and New Zealand, December 2001.
15. Sallach, D. and C. Macal (2001). “The simulation of social agents: an introduction”, *Social Science Computer Review* 19(3):245–248.
16. Macal, Charles M. and Michael J. North (2006). “Tutorial on Agent-Based Modeling and Simulation Part 2: How to Model with Agents”, *Proceedings of the IEEE 2006 Winter Simulation Conference,* Monterey, CA, 3-6 Dec. 2006.
17. North, M.J., et al. (2010). Multiscale Agent-Based Consumer Market Modeling, Complexity**,** Volume 15, Issue 5, pages 37–47, May/June 2010, Wiley Periodicals, Inc.
18. Rigby Darrell (2011). The future of shopping. *Harvard* Business Review. December 1, 2011.