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Multi-Agent-Based Modeling of Deshopping Behavior Considering Two or More Shops or Web Sites

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***Abstract* - The focus of this research is on simulation modeling and a multi-agent-based system for consumer deshopping behavior. Most recent work on deshopping analysis has been focused on case studies and theory building. This study intends to propose a decision framework and computational model of deshopping that combines consumer purchase with return behavior. A multi-agent system, together with simulation and associated functions, are created. The rich detail provided by simulation modeling can contain a hybrid marketplace as elements of the retail environments and two or multiple firms, competitors, Web sites, etc. To develop this computational framework and model, several integrative frameworks for evaluating deshopping, behavioral intention, rational choice, shop or Web site choice, opinion dynamics, return leniency are employed. The simulation and modeling allow firm responses to deshopping to be simulated over time. Return leniency modeling allows firm responses to be analyzed as well. The simulation model provides a bird's eye view of the presence, impact, and growth of consumer deshopping behavior and its effect on return policies and customer loyalty.**

Keywords: Deshopping, Simulation, Multi-Agent-Based Modeling, Retail Marketing, Consumer Behavior

I. INTRODUCTION

Deshopping is regarded as an abuse of return policies in the retail marketing literature. It is known under a broad umbrella of terms such as retail borrowing [1], Jay customers [2], fraudulent borrowing [3], unethical retail disposition [4] among others. In deshopping, the customer called "deshopper" is the party that tries to get financial and non-financial gain by willfully and knowingly violating the terms of the service through sheer malevolence. The advent of the Gig economy and associated disruptive business models have been the positive outcomes of advances in information technology and the Internet for consumers everywhere. As the businesses and consumers have moved online so has frauds. This channel has introduced the possibility of wide scale faceless crimes being committed against the members of the online retail industry [5].

II. LITERATURE REVIEW AND DISCUSSIONS

A. Deshopping

First stream of the discussion is centered on deshopping. Deshopping exists not just offline channels, but also in the online channels where it is easier to defraud. Reference [6] studied the impact of different delivery patterns and return policies on curbing consumer deshopping behavior. The findings of the study indicated that delivery patterns and return policies have a bearing on consumers return behavior. For the deliberate deshopper, free return policies offered by retailers help reduce the total spending by the amount of the delivery cost which provides motivation to continue deshopping. Generous return policies act as an enabler for deshopping behavior. The references [6, 7] researched returns without categorizing them into legitimate and fraudulent categories. The research highlights that customers who return items regularly represented spent the most overall and frequently, while returning the most or all the time. So, altering the targeted return policies for frequent retuning customers can control such behavior [6].

B. Modeling Human Behavior (MoHuB) framework

The modeling of deshopping is the focus of the second stream of discussions. MoHuB framework is focused on aspects of decision making and human-environment interactions. The MoHuB framework can accommodate multiple theories inside it interchangeably. Simulating human interaction when most models are based on empirical correlations can be challenging. Even though rational choice is not the most recent theoretical breakthrough, it is possible to incorporate it in the framework.

MoHuB framework implementation is based on the rational choice theory-based mapping. In the rational choice theory implementation, the goal state focuses on self-interest. The goal maximization is mapped to a utility function with clear understandable values. Each agent can have individual skill sets and possess complete information about the environment. The agent knows all the options available to it and is only constrained by the agent's skillset and financial assets. Thus, utility maximization is the goal of the agent. In most cases, a rational actor does not become affected by the outside systems feedback since all information is accounted for. In some cases, however, the actor can be designed to accept feedback from the system for future time steps [8].

C. Rational choice

Rational choice perspective presented by [9] states that any lawbreakers thoughts can be considered as a formal decision where he or she balances the potential gains of a successful crime against potential losses or costs if unsuccessful. This line of thinking justifies crime as something only worth committing if returns are good. The reference [10] provides proof from interviews which supports the point of view that frauds are committed even when the odds are overwhelming and tend to focus on the rewards. The reference [11] states criminal behavior as the result of rational agents trying to augment their gains. So, criminals are driven to increase their material gains or seek peer recognition through unlawful activities not forced into by societal conditions or circumstances. The reference [12] stated that the value of an activity was rooted on a person's concept of gain from that behavior in [13]. The entire decision process needs considerable information which is gathered as the process goes through its various stages towards its completion. The reference [14] illustrated two important keystones in the rational choice theory. Firstly, the approach of rational choice theory meant most of the time offenders employ a cost-benefit approach in all offending and non-offending choices. This approach requires an offender to collect all available information about these risks, rewards and costs and based on their value to decide whether to commit any crime or non-crime action. The benefit (B) that a person accrues from an unlawful activity, the subjectively expected probability of being caught (p) and the costs (C) that one expects to pay defined as "subjectively expected level of penalty "are important factors in a person's decision making for crime". Baker explains the expected utility (EU) as the following: $EU\ [S] = B - pC$.

If $B > pC$ then there is a higher chance of a crime with Expected utility $EU[S]$ being positive. The probability p is a subjective expectation which varies across individuals. There is little information available to anybody how likely a crime is likely to be discovered and a criminal apprehended. The value of the subjective probability changes based on several factors such as individual's knowledge and experience and their peer groups as well as social class. For any criminal activity, the reference [11] considers the probability of success being the reverse of being caught $1 - p$. Thus, from the perspective of Subjected Expected utility (SEU), the probability of success q is associated with the expected benefit of the offence and the probability of getting caught associated with the cost of getting caught $SEU\ [S] = qB - pC$

Where $SEU[S]$ is the subjectively expected utility from the offence S, q is the subjective probability of the crime, B the subjective value of the benefit, p the subjective probability of the degree of the penalty and C the subjective value of the degree of the penalty.

If $qB > pC$ then $SEU[S]$ is positive and a crime might be committed. These four variables describe illegal activity. Different valuations of these variables are subjective difference among individuals of benefits, utility, costs, risk, and success. P is a continuous variable with a value between 0 and 1. For $p = 0$, expected utility $SEU[S]$ becomes qB and the value of qB will affect whether someone commits a crime. If p =1, then utility becomes $qB - C$. If the value of qB is greater than C, then despite the cost, the crime is carried out. This follows that breaking the rules can be justified even if they are fraught with risk and attitude towards that risk do not count against it. Unfortunately, economic explanations of illegal behavior do not consider norms and their internalization. Actors choose a certain behavior if it its positive in their estimation and they expect their peers to support this behavior. This provides the modeling of rational choice a different dimension. We assume that norms do influence the utility and pay off received by actors. N will be the deterring effect of internalized norms and ϵ is the error term [15]. The rational choice models of crime are often tested using regression analysis.

$$\text{Deshopping Intention} = \beta_0 + \beta_1 q + \beta_2 B - \beta_3 p - \beta_4 C - \beta_5 N + \varepsilon \ \ldots \tag{1}$$

In this model q , B , p and C will are all treated as parameters. This additive modeling can be improved by including an interaction term pC since this signifies p and C are linear and independent. But in the actual world, the effect of sanctions is dependent on the detection probability and thus should be impacted by it. So, B and C are treated as parameters only and q and p should be treated as weights.

$$\text{Deshopping Intention} = \beta_0 + \beta_1 q + \beta_2 B + \beta_3 (qB) - \beta_4 p - \beta_5 C - \beta_6 (pC) - \beta_7 N + \varepsilon \ldots \tag{2}$$

These are the models we will be testing. There are even more complete and sophisticated versions of this equation available which solve the problem of treating costs and benefits as independent of each other. Unfortunately, the modeling will make operationalizing the parameters in a simulation extremely challenging. So, we only model equations (1) and (2) [16], [17]. We accept that this as the limitation of this study.

D. Computational model of deshopping

Computational models can be used to predict future outcomes, can be employed as a testbed for exploratory concepts, transform data and raise queries about activities [18]. The reference [19] suggests a computational model shows up often as an algorithm outlining carefully all the steps that will be. The reference [20] argue that computational model can help realize its promise by helping organizational theory and behavioral research. The reference [21] describes the modeling process into a computational model. The process starts with the conversion of the theory into code of the computational model. The conversion process transforms the terms and associations between the theory elements into viable structural relationships, variables, and starting conditions for the model. The model is turned into a probabilities and conditional statements to be used in the appropriate simulation platform.

III. UNDERPINNINGS OF THE MODEL

Our computational model incorporates research findings from deshopping, return policy leniency, shop choice model, information propagation, churn analytics, and social networks and provides a visible and interconnected framework towards deshopping modelling. The underlying motivation to conceptualize deshopping leads us to propose a computation agent based deshopping model that incorporates multiple theories underpinning deshopping and return policy behavior of shoppers and simulates the effects in a multi agent multi shop setup. The model is an expansion and continuation of the single shop model [22].

The multi shop model offers the following features:

A clear transparent framework for the modeling of deshopping Behavior of agents. Incorporates reasonable assumptions when converting complex interactions into rules and relationships. Focuses deshopping's dynamic factors into model reducing the socio-economic variables, rationality, motivational factors and consumer decision making process into agent sets, rules and assumptions. It also makes deshopping Behavior the central tenant of the model and makes it possible to show and record the situations under scenarios where it occurs. It allows degree of predictability to deshopping modeling. The modeling follows PDCA (Plan-do-check-at) cycle specified by [23] in the translation of the deshopping model into a computational model [24].

Deshopping presents a unique challenge for retailers which presents cost implications from profitability, inventory management, sensitivity, and complexity stand points. Being able to model deshopper and shoppers in a dynamic environment with rich spatial details, company level data and behavioral rules can provide information and insights for strategic management decisions. The entities that constitute the deshopping process are

Deshoppers who are shoppers who come to shop. They may have premeditated notions of using deshopping to privately benefit from the shopping trip. They capture extra surplus from the trip by keeping the item and leave retailers worse off. They do not always do it, do not always succeed. But if the retailer is lax with returns, it happens. When it does not come off, they tell the whole world. When it comes off, they tell their friends. They form social networks with other shoppers, sometimes even deshoppers.

Shoppers are just what they say they are. Normal people who come to buy from retailers. They occasionally return things too. They live in social groups with another shopper and sometime even deshoppers. Who does not have a dark sheep in the family? They try to maximise their own utilities. They also have some idea of deshopping too. Some have not tried ever. Some have seen others do it.

Retailers are present as a pair of shops who serve these two groups of shoppers and deshoppers while they compete.

In the model, the Turtle type agent breeds shoppers and deshopper and patch type agent shops. The dynamic nature of NetLogo means creating shopper and deshopper agents is very simple. Creating new retailers is simple as well. But changes to code are necessary. But it can be expanded to include many more retailers. Agents are created on the fly, so numbers are not a major concern. The reference [25] define agents and the behavior and interactions as the main feature of the program.

The presentation of agent behavior is given in Fig.1.

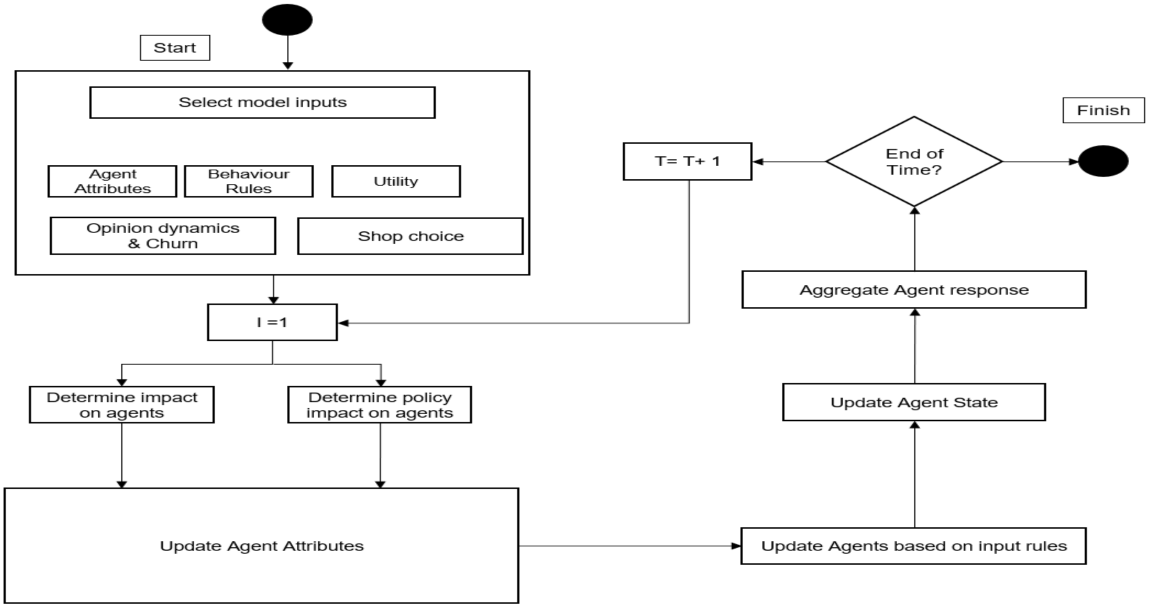

Fig.1. Agent behavior representation (Adapted from [26]).

The agent behavior representation shows how agents update their attributes in the real world based on the impact of their decisions. Here the perceived behavioral options are based on their goal sets. Shopper and deshopper agents both show both reactive and proactive decisions. Churn and spawn decisions are reactive, while other decisions such as buying and deshopping are deliberate.

A. Graphical User interface

The graphical user interface (GUI) of our multi-agent model is shown in Fig.2.

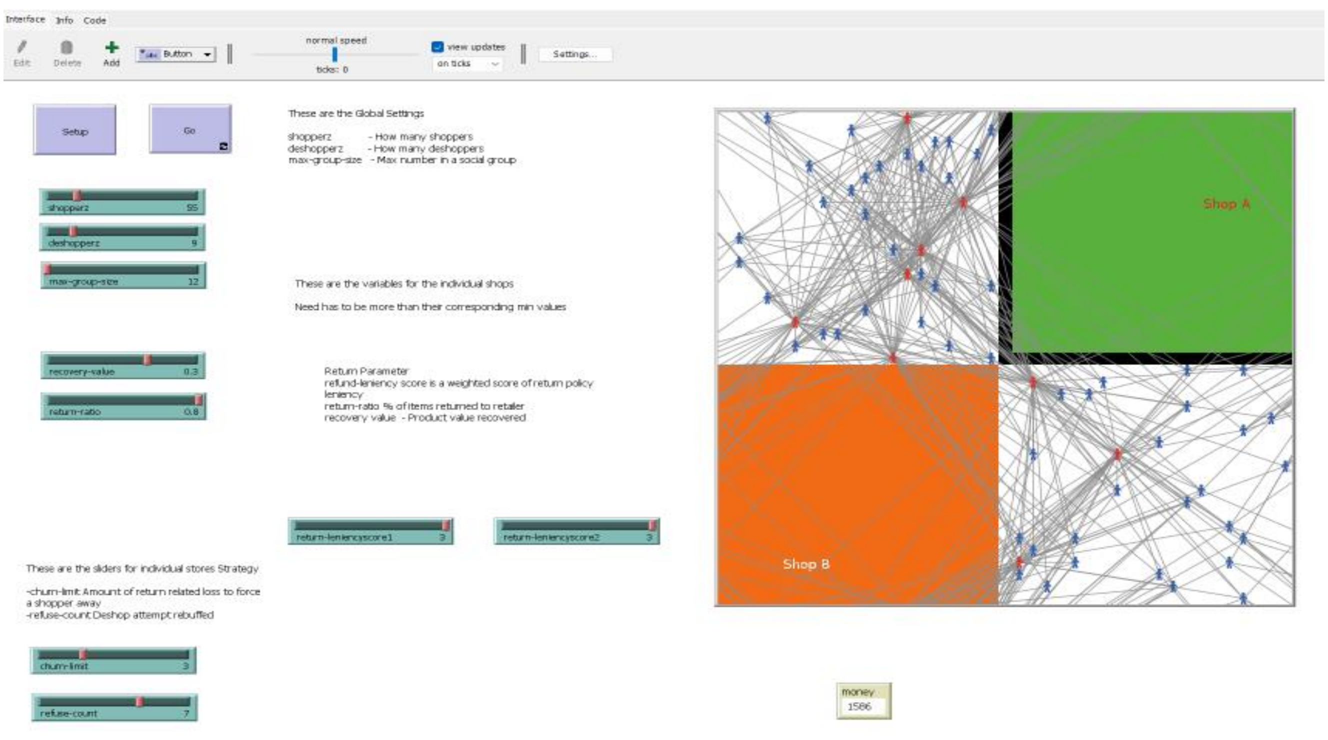

Fig.2. Screenshot of GUI of Netlogo ABM model.

B. Agents and agent behavior

Agents are the central focus of our deshopping model. Agents will allow us to model a deshopping system, code behavior rules and study its behavior. The implementation of the agent based multi shop was done in two stages. Initially, a single shop model with some of the parameter sets discussed above was created and tested. This was the basis of the single shop model [22]. The new model has similar shop features. But possess much more detail and richness with first and secondary data as well as detailed human behavior modeling. An agents state allows it to choose between different perceived behavioral options. The set of perceived behavioral options can also change and update over time.

C. *Human decision modeling*

Out of many perceived behavioral options the agent takes the one with the highest utility. These are internal decisions. There are decisions taken which react with the outside world such as contact with social environment where other shoppers exist and interact. The main group of agents deshoppers, shoppers, retailers all interact based on their goals, values, knowledge, and assets. Based on these the best perceived behavioral option is selected. The social & biophysical layer in the MoHuB framework is where other shops and other agents in the social group are located as well.

D. Structural elements of agents

A shopper or a deshopper will choose a behavioral option based on specific goals, values and rules. Rational choice agents always try to make optimized decisions. All the decisions have costs and payoffs. Buying decision is a combination of shop choice-based utility and deshopper utility. Both are utility maximizing operations. Shop choice equation is based on the workings and data from [27].

Deshopping intention

Deshopping intention is calculated based on a binary logistics regression [28] calculated at run time based on primary data collected.

Deshoping equation

$$\beta_0 + \beta_1 q + \beta_2 B - \beta_3 p - \beta_4 C - \beta_5 N$$

Return Intention

The intention to return a product is based on industry return rates of 20% on all purchases. For deshoppers, returns are deshoping attempts.

Churn intention

The decision to churn due to frequent deshopping fails and return fails is based on a simplified churn limit.

Spawn

A shopper turns into a deshopper.

Shop choice decision

The shop choice decision is based on the utility. The consumers shop choice function is

$$\Pr(y_{hsv} = 1) = \frac{exp^{(Fixed_{hsv} + variable_{hsv})}}{\sum_{i=1}^{S} exp^{(Fixed_{hsv} + variable_{hsv})}}$$

Where $Utility_{hsv} = [\,\alpha_{s1} + \alpha_{s2} * Experience_{hv}] + [\,\beta_6 * Online\_loyalty_{hs} + \beta_7 * Offline\_store\_preference_{hs} + \beta_8 * Offline\_store\_preference_{hs} * Price\_integration_{hs} + \beta_9 * Offline\_store\_preference_{hs} * Assortement\_integration_{hs}\,] + [\,\gamma_1 * Experience_{hv} * Price_{hsv} + \gamma_2 * Experience_{hv} * Assortement\_size_{hs} + \gamma_3 * Experience_{hv} * Assortement\_composition_{hs} + \gamma_4 * Experience_{hv}\_hv * Price\_integration_{hs} + \gamma_5 * Experience_{hv} * Assortement\_integration_{hs} + \gamma_6 * Experience_{hv} * Online\_loyalty_{hs} + \gamma_7 * Experience_{hv} * Offline\_store\_preference_{hs}\,]$

Since the model was based on same price (with price = 1) effect, we decided to ignore the price effect from the model. Assortment effects are also assumed similar (=1) since the shops were designed with only 1 type of item. Assortment integration (=1), price integration (=1) and assortment integration (=1) are also similar across both shops. These are based on our shop assumptions. This does mean the effects would not be same as it was in the study. Most of the drooped interaction effects were not statistically significant. But that is a major limitation of the study.

Store loyalty:

Weighted sum of loyalty in the previous trip (v-1) for a household equals 1 if the last purchase was from the store, 0 otherwise. Weighted with a decay parameter λ = .7. starting value = .7 for the store chosen and .1 for other ones.

$$Online\_loyalty_{hsv} = \lambda * Online_{loyaltyOnloy_{v-1,hs}} + (1 - \lambda) * LP_{hsv}$$

Store Experience

Reference [29] frame online buying experience as a weighted sum of previous in the period $b^{c}_{i,t-1}$ with weight equal to λ (between 0 and 1, authors used .7 as the value) and based on all the previous periods (s= 1, 2, 3, ..) to capture the decay effect. Starting value of Exp^{c}_{it} is based on an initialisation period of 26 bi weeks.

$$Exp^{c}_{it} = Exp^{c}_{it} * \lambda + (1 - \lambda) * b^{c}_{i,t-1}$$

$$\sum_{s=1}^{s=t-1} \lambda^{t-s} * Exp^{c}_{i,t-1} + \lambda * b^{c}_{i,t-1}$$

Experience = $\sum_{q=1}^{q=v-1} \sum_{s=1}^{s=2} M_{h,s,p-1} * \delta^{p-q}$ is the weighted sum of previous online purchase in the estimation period over all the stores weighted with a decay effect 0.5 and starting value = 0.

Store preference

The return rule is based on industry return standard we have chosen.

$Offline\_store\_preference_{hs}$ is the proportion of sales per household h for each store s in the initial period = $sales_{hs}$ / $sales_{h}$

$Loyalty$: Reference [29] defines store loyalty as $Loyalty_{hs} = \frac{N_{hs}+\frac{1}{S}}{(N_h+1)}$

Where N_{hs} is the number of visits household h makes to the store chain s during the initialization period and N_h is total number of store visits by household h during that period. So, a ratio of a single shop visits over total shop visits.

Influence propagation

The following is the deshopper influence propagation model that we propose for churn modeling will be a simplified version of the model.

A deshopper initiates the spread of influence to his social network based on his unsuccessful deshopping experience.

1. Agents who have favourable views of the deshopper can be influenced. Those with unfavourable views of sender and deshopping takes none. Only shoppers in the same group are affected. This is based on norm values normalized between 1/-1 using $\frac{Norm_{max} - Norm_{actual}}{Norm_{max} - Norm_{min}}$. If influence comes from an agent with more influence, then the influence is accepted. Someone who has lower scores will not be able to influence.
2. An agent can be influenced by nodes in its social group.

If customers are already unhappy then they can be convinced easily to churn.

Return Leniency

This controls the return leniency levels at the retailer. The equation is modelled based on binary logistic regression formulated based on primary data.

$$P\ (deshopping) = \frac{e^{(\beta_0 + \ return\ leniency * \beta_1\ )}}{1 + e^{(\beta_0 + \ return\ leniency * \beta_1\ )}}$$

IV. CONCLUSIONS

In order to fill the gap identified in the deshopping literature, our work on multi-agent-based modelling and simulation of consumer deshopping behavior has considered two or more firms, competitors, shops or Web sites.

The computational and simulation model of multi-shop deshopping demonstrates that a simulation model based on real data and theory can be developed that shows the impact of deshopping as daily dilemmas for retailers with generous return policies. This is of interest to both practitioners and researchers from operational and strategic point of views. The paper highlights how retailers can balance between minimizing the deshopping and allowing returns.

In order to overcome the limitations, this study can be extended in multiple ways. It can adopt other behavioral theories in the MoHuB framework to increase the validation and verification of the model. Other theories of return leniency and influence propagation can be included in our future work. In addition, cost elements and their effects may also be measured.

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