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MODELING CONSUMER DECISIONS ON RETURNING END-OF-USE PRODUCTS CONSIDERING DESIGN FEATURES AND CONSUMER INTERACTIONS: AN AGENT BASED SIMULATION APPROACH

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ABSTRACT
As electronic waste (e-waste) becomes one of the fastest growing environmental concerns, remanufacturing is considered as a promising solution. However, the profitability of take back systems is hampered by several factors including the lack of information on the quantity and timing of to-be-returned used products to a remanufacturing facility. Product design features, consumers' awareness of recycling opportunities, socio-demographic information, peer pressure, and the tendency of customer to keep used items in storage are among contributing factors in increasing uncertainties in the waste stream. Predicting customer choice decisions on returning back used products, including both the time in which the customer will stop using the product and the end-of-use decisions (e.g. storage, resell, through away, and return to the waste stream) could help manufacturers have a better estimation of the return trend. The objective of this paper is to develop an Agent Based Simulation (ABS) model integrated with Discrete Choice Analysis (DCA) technique to predict consumer decisions on the End-of-Use (EOU) products. The proposed simulation tool aims at investigating the impact of design features, interaction among individual consumers and socio-demographic characteristics of end users on the number of returns. A numerical example of cellphone take-back system has been provided to show the application of the model.

1. INTRODUCTION
The term e-waste is commonly used to refer to old electronics that are obsolete or no longer wanted by end users [1],[2]. However, most of these products can be refurbished, recycled or reused in the secondary markets [3]. E-waste is the point of concern compared to other forms of waste due to their high volume and the toxicity of hazardous materials they contain [4]. However, e-waste is attractive from an economic perspective. Given the volume of e-waste, over 60% of it is made up of precious metals which can be extracted in recycling and recovery processes [5]. In addition to metal recycling, remanufacturing is another profitable solution, even in the presence of uncertainties associated with the nature of remanufacturing process [6].

Although e-waste recovery is attractive from an economic perspective, the remanufacturing profitability does not only depend on the OEMs policies. This profitability is influenced by consumer behavior and the variation it brings into the e-waste return stream in terms of quantity, quality and timing of returns. Planning for used products recovery requires an accurate prediction of waste generation. There are many factors influencing the volume and condition of returns including consumer choice decisions on whether to keep EOU products in storage or return them back to the waste stream. A considerable number of prior studies, most of which are survey based analyzes, have been focused on identifying those factors. However, there is a lack of research on developing models that predict consumer behavior and choice decisions on EOU products.

Development of models with anticipated prediction accuracy with regard to the electronics design features, socio-demographic, economics, and risk attitude profiles of final consumer as well as the OEMs design policies is quite challenging. Therefore, this provides motivation to develop simulation models which do not have the limitations of analytical studies.

The main objective of this paper is to create an Agent Based Modeling (ABM) framework with the aim of simulating consumer choice decisions on returning back used items considering product design attributes and consumers' socio-demographic information as two main groups of factors. Moreover, employing the capabilities of ABM in integration with DCA technique, a tool has been developed to dynamically model the impact of interactions between individual consumers and the information they receive from their peers on the decision they make.

The amount of time people keep their unwanted products in storage is one of the challenging obstacles toward profitability of remanufacturing operations. The storage time results to product obsolescence. The simulation results provide designers some insights on the impact of product design features on the storage time and the rate of return. Adjustment of product design life, the obsolesce rate, buyback price, product modularity and adding features to facilitate end-of-use return are among those insights.

The rest of this paper is organized as follows: Section 2 provides a review of related literature on the factors controlling the rate of e-waste return. Section 3 explains the components of simulation method, the factors included in the model and the mathematics behind simulation. Section 4 provides a numerical example and finally Section 5 concludes the paper.

2. LITERATURE REVIEW

There are a few studies that specifically targeted the e-waste stream analysis and return estimation [7]. Yu et al. [8] applied a logistic material flow analysis to estimate the amount of obsolete PCs in developed and developing countries. They showed the number of discarded PCs for developing countries will exceed that of developed countries in 2016-2018. Kwak and her colleagues [9] analyzed a database of incoming used electronics to an e-waste collection site and concluded that processing different brands and generations of products is an obstacle in take back recovery systems. They emphasized on the impact of design features on the variability in e-waste stream. Wang et al. [10] used a multivariate input–output analysis technique to improve the quality of input data to better estimate e-waste generation. Chung et al. [11] investigated the impact of producer responsibility scheme in controlling e-waste generation in Hong Kong. There are similar studies which focused on analyzing e-waste situation in China and Philippines [12–15]. Case studies with similar approaches of different geographical regions including Asia [16], USA [17] [18], European countries [19,20] or global studies [21] have been reported.

Araújo et al. [22] pointed out the lack of sufficient reliable data in estimation of e-waste generation. They showed the most important factor in estimating the e-waste stream is product lifetime. In addition to product design features and basic uncertainties in product lifespan, there are some other factors which make estimating the actual return stream even more complicated. Initial price paid by consumers, consumer's cognitive biases, product size, and incentives offered by OEMs are among those factors. The effect of consumer as a decision maker should not be neglected in estimating the return rate. Sabbaghi et al. [23] reported that consumers often store their used product before returning them back. The factors that impact consumer decisions have been categorized under three groups:

- Environmental regulations
- OEM policies and product design attributes
- Socio-demographic characteristics of consumers
- Consumers risk attitudes

Environmental Regulations: Since e-waste has been recognized as a potential threat to human health [24] [25], a considerable number of regulations, programs and standards such as Basel Convention have been established to ameliorate the issue of e-waste hazardous materials [26,27]. The concept of Extended Producer Responsibility (EPR), which forces manufacturers to take the responsibility of their products for the whole life cycle, is an example of regulations that influence product returns [28].

OEM Policies: The decision made by OEMs on product design features influences the return rate. Product size, weight and price are among those decisions. In addition to decisions made at the early stage of design, OEMs can also control the return stream by offering incentives. Old-for-New exchange programs are examples of such policies.

Socio-demographic characteristics of consumer: Although less attention has been given in the literature to the role of consumer behavior in estimating the return rate, it does play an important role. Consumer behavior toward discarding used items can be modeled as a decision making process in which the consumer will decide whether to sell, return or store their product after usage. *Socio-demographic* information of end users cannot be neglected in analyzing this behavior. Consumers' income and education levels are examples of these characteristics.

Consumer risk attitude: In addition to socio-demographic information, consumers risk attitudes and cognitive biases are another group of factors. Among the list of cognitive biases, loss aversion should not be neglected. The concept of loss aversion was first introduced by Kahneman and Tversky in the context of a reference dependent utility model in their prospect theory, which proposed that the value is normally steeper for losses than for gains [29]. There are several studies that targeted the reference dependent preferences and used the loss aversion concept to model consumer choices [30–34]. We believe this concept can be employed in analyzing consumer behavior in discarding their used items since a more loss averse person is less likely to return the product rather store it.

Although the number of studies focused on estimation methods is limited, there are a considerable number of studies aimed at capturing factors that influence the return or recycling behavior. These studies are mainly survey based. Yin et al. [35] conducted a survey to find out consumers' behavior and willingness to pay for recycling of obsolete cell phones. They concluded that the average service life of cell phones is shorter than the design life and more than 47 percent of the consumers keep their old cell phones in storage rather than recycling them. In addition, they showed education, region and income level are among the main factors affecting the consumers' willingness to pay for recycling. In a similar survey-based study, Afroz et al. [36] showed only 2 to 3 percent of the consumers in Kuala Lumpur recycle their electronics, while 52.5 percent of them are willing to pay for improving the e-waste management plans. Manomaivibool and Vassanadumrongdee [37] proposed that a standardized buy-back program can improve the formal recycling sector in Thailand. It can also motivate consumers to dispose their products rather than store them. However, it is not sufficient to stop people from selling their products to informal waste dealers. Darby and Obara [38] conducted a large scale postal questionnaire and semi-structured interviews in Cardiff and showed a lack of awareness regarding the recycling and disposal of small electronic waste at the time of their research. They concluded that the majority of small electronics were not being recycled. Annual income and gender were the factors included in their model. McCarty [39] proposed that consumer values do not directly influence behaviors but they affect attitude toward importance of recycling, which indirectly affect the recycling behavior. Colesca et al. [40] showed the factors influencing people's willingness to attend waste management programs are varied depending on the country they live. Li et al. [41] also proposed that educational level plays the major role in consumers' willingness to pay for waste management programs in China. In a similar survey-based study in Sweden, Miafodzyeva et al. [42] suggested that the attitude toward recycling has influence on the recycling behavior. In addition to the above mentioned factors, product design features have been discussed in the literature as factors affecting consumer behavior. Sabbaghi et al. [23] analyzed a dataset of used hard disk drives and showed the impact of brand, consumer type and design characteristics such as hard drive size on consumer behavior toward product utilization and storage.

In addition to survey-based studies, there are several studies that applied discrete choice analysis techniques to quantify consumer choice decisions. Milovantseva and Saphores [43] used multivariate nominal logit and investigated the effect of waste management policies on consumers' decisions toward recycling, reusing, disposing and storing TVs and cell phones. Dwivedy and Mittal [44] studied the same thing in India and concluded that income, recycling habits and economic benefits are the major factors. In addition, they suggested that pay afterwards take-back financing programs will be effective.

Reviewing the above mentioned literature reveals several points: Although various questions have been tackled in the literature ranging from willingness to pay for recycling or participate in return programs [41,44] to socio-demographic factors that influence consumer decision [37][40], there is not sufficient research on how to use these factors to estimate the return rate. DCA techniques can be used to quantify consumer choice probability based on the identified factors. However, the basic idea in DCA is to fit regression models to discrete outcomes and find the significant factors influencing consumer's choice and their corresponding coefficients. Although DCA is a strong tool for studying discrete outcome events, it does not consider interconnection of individual consumers and how it will influence the choice probability. In DCA each observation is considered as a single independent decision making progress which is not completely true in the real world. In reality, consumer's decision on participating in recycling programs or even their awareness of such opportunities is influenced by other consumers' decision and may change dynamically over time. It is not a far-fetched idea to consider the fact that an individual is probably more aware of recycling programs if they are in contact with other people who already have participated in such programs. In addition, despite the fact that the impact of design features has been pointed out already in the prior work, research is limited in quantifying this impact.

To cover the above mentioned points, simulation has been considered as a promising solution. An integration of Agent Based Simulation (ABS) and DCA technique has been employed to model individual consumers' choice regarding EOU destiny of used electronics while considering different design and socio-demographic factors. Building such simulation tools paves the way for achieving a more comprehensive understanding of consumer behavior and its impact on the e-waste return rate.

The current work is different from available literature in two ways: First, in the new application of ABS platform and DCA to model consumer choice decision (store, sell, return, etc.) toward end-of-use products, second, through expanding the DCA technique by including the impact of consumer interactions and other decision makers' choices on the decision made by each agent.

3. AGENT BASED MODELING FRAMEWORK

As illustrated in the literature, estimation of e-waste stream and recognizing consumer choice decisions include many complexities. Simulation models can provide us a realistic projection of the population under study and the interactions among many factors that influence their decisions. In addition, using optimum seeking algorithms behind simulation models helps decision makers investigate different scenarios and study the current and future behavior of system [45].

In agent based modeling, the interactions among components play a pivotal role. Systems are characterized such that global properties cannot be deduced by looking at only how each component behaves. ABM follows a bottom-up approach, while conventional simulation methods such as Discrete Event Simulation (DES) follow a top-down approach. Unlike DES, in ABM agents are capable of decision-making on their own. Each agent individually assesses its situation and makes decisions based on a set of decision rules. This characteristic of ABM enables decision makers to focus on the microscopic individual behavior as well as the macroscopic pattern of the epidemic emerging at the larger scale. Agents are capable to change their states and communicate based on simple rules [45]. Particularly, agent based simulation is an appropriate tool for modeling population studies.

3.1. Agents

The diverse decision makers in the e-waste recovery system are represented as 'agents.' The simulation environment consists of different types and numbers of agents which have their own set of objectives, behavioral patterns and, decision-making rules. Agents interact with each other in either a predefined or random network. Each agent is able to update their status or make decisions based on the information they receive from other agents.

Anylogic 7 University software has been used to develop the simulation models. The general procedure to build models include: 1) identify agents and players of the take-back system, 2) determine agents' attributes and behavior [decision rules: both rational and subjective parameters], 3) formulate algorithms based on agents' attributes and behaviors, 4) implement the algorithms, 5) observe and analyze the system emergent properties.

Four types of agents are considered in this paper: 1) Consumers, 2) Manufacturer, 3) Collection Centers and 4) Products. Figure 1 shows the simulation environment in Anylogic software. The nodes represent consumer agents and the links between them show corresponding connections.

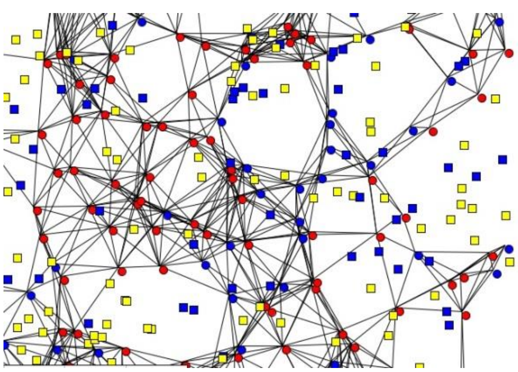

Figure 1. The simulation environment: agents and their networks

Consumers:
Consumers are agents which use the product. Once product reaches to its end-of-use stage, consumer should decide on what to do with it. They have four options: 1- Store, 2- Return, 3- Sell to second hand market and 4- Throw the product away. Once the consumer decides on what to do with the EOU item, he informs the associated product agent of his decision. The product agent then changes its state based on the update information received from the consumer. Figure 2 illustrates the consumer's states in the model.

Products:
Products are assigned to the consumer agents based on the sales trends information over time. This represents the product purchase process by the consumers. It has been assumed that each product will be assigned to one consumer over a time period following a distribution (i.e. uniform distribution over six months). The state of each product changes from "usage" to one of the four above mentioned options (stored, returned, sold to second hand market and thrown away). If the product is thrown away, it will be considered as waste or trash.

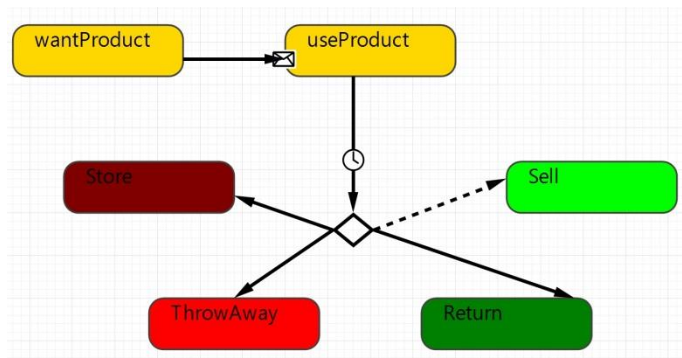

Figure 2. Consumer decision states in the simulation

Collection Centers:
Collection centers receive discarded items from the consumer. In other words, if a consumer decides to return their product to the manufacturer they have to return it to a collection center.

Manufacturer:
Manufacturer is an agent who defines the product design attributes as well as the corresponding buyback price for each design.

3.2. Discrete Choice Analysis

This section describes DCA technique which is the basic logic behind the decisions made by consumer agents. DCA is a probabilistic choice modeling technique originated from mathematical psychology which was developed simultaneously by economists and cognitive psychologists. DCA is often used to capture market demand of specific design alternatives by capturing individual choice behavior. DCA is a disaggregate approach, which uses data of individual customers as opposed to aggregate approaches which use group averages in modeling market share of each alternative as a function of the alternatives' features and the socio-demographic attributes of the group of customers [46]. The concept of DCA has been employed in this paper to calculate the choice probability for each EOU option.

Depending upon the degree of heterogeneity, different variants of DCA models have been developed including Multinomial, Nested, Mixed Logit, and Ordered logit [46]. These models are based on this key assumption that in each choice situation, the consumer chooses the alternative with the highest utility.

Multinomial Logit models consider the consumer choice deterministic utility based on a linear combination of attributes [46]:

$$U_{in} = \beta_{0i} + \beta_{1i}S_n + \beta_2 A_i + \beta_3(S_n.A_i) \quad (1)$$

Where U_{in} is the utility of choice i for consumer n, β_{0i} is an alternative specific constant, β_{1i} is an alternative specific coefficient, S_n denotes the socio-demographic attributes of consumer n and A_i denotes the attributes of alternative i. It is assumed that the consumer will choose alternative i if their utility for such choice is at least as large as other choices utilities. In multinomial logit model, the coefficients (β) are considered the same across all the consumers and the heterogeneity is modeled by considering socio-demographic characteristics of each individual.

However, Mixed Logit models extend the heterogeneity consideration by assuming that the coefficients (β) can vary over the population for each person [46]:

$$U_{in} = \beta_{Ai}A_i + \beta_s S_n + \beta_{A.S}(S_n.A_i) \quad (2)$$

Where β_{Ai} for every consumer is random but β_S is fixed. The concept of DCA method has been extended in this paper using Agent Based Simulation by varying the coefficients (β) over the consumers and also considering real time assessment of attribute values derived from consumer interactions. The following points have been considered in this model:

- Instead of considering random β_{Ai} for every consumer and fixed β_S, all the coefficients (β) for different attributes are varied over the individuals. They are randomly distributed.
- Several factors including peer pressure and awareness represent the interaction between different consumers and should be calculated in real time during simulation.
- There are some attributes/factors like the manufacturer incentive or market price which are not fixed and should be calculated dynamically over time.

3.3. Decision Variables

As explained in previous section, the decision process is based on discrete choice model which computes the utility of each alternative for every individual consumer. Two different scenarios and two cases within each scenario have been modeled in this paper. The difference between two scenarios is in the logic behind modeling the consumers' interactions. First scenario uses the density of returns in the network of peers for each consumer directly. However, in the second scenario this density is the criterion to categorize consumers in different subgroups. For both scenarios two cases have been considered (with and without consideration of the interactions). The details of each scenario are discussed below.

In the first scenario, the following factors are considered: *education level* (X_1), *income* (X_2), *peer pressure* (X_3), *consumer awareness* of recycling programs (X_4), product *data security* (X_5), *second hand price* (X_6) the *buyback price* (X_7) offered by manufacturer and the *accessibility* (X_8) to collection centers. *Education level* and *income* are the socio-demographic characteristics which are mostly agreed upon in the literature. Four different levels have been assumed for *education* where it is assumed that consumers with higher *education levels* are more likely to be environmentally concerned and return their product. For *income*, a log-normal distribution has been considered. Moreover, it is assumed that higher *income* decreases the motivation provided by the monetary benefit of selling products in the secondary market or returning the product and thus increases the chance of storing or throwing the product away.

Each agent is connected to two networks: peer network, and awareness network. At the beginning of experiment each agent is connected to a random number of other consumers (between 1 and 10). This is the network of peers. The density of product returns in the network of each consumer influences their decision on whether to return or not. While peer pressure presents the impact of the decision made by relatives or friends of each consumer on his or her decision, consumer awareness represents the interaction of consumers in a region. This is a distance based network in which increasing the density of product returns from consumer's vicinity raises the chance that the consumer is aware of available recycling programs. The values for *peer pressure* and *awareness* are calculated in real time during the experiment and present the effect of consumer interactions on his decision. *Peer pressure* is the density of the returns in the network of consumer peers and *awareness* is the density of the returns in the network of consumer vicinity as described in Equations (3) and (4). So in other words *peer pressure* represents the effect of friends and relatives and *awareness* network shows the effect of neighbors who share the same collection facilities or have similar access to collection sites located in a region.

$$peer\ pressure = \frac{number\ of\ returns\ from\ peers}{number\ of\ peers} \quad (3)$$

$$awareness = \frac{number\ of\ returns\ from\ neighbors}{number\ of\ neighbors} \quad (4)$$

One reason why people are reluctant to return their products[1] is due to their concern about data privacy and security. Data security is a design feature controlled by manufactures. A *data security* index has been defined for each product. An example of cellphone take back system has been modeled in this paper. It is assumed that the cellphone has a modular design such that consumers can remove the internal memory of their cell phones before returning them back. This ensures consumers' data

[1] This is product dependent and applies only to some electronics.
We consider the case of cell phones which privacy concern has a big impact on consumer's decision.

security such as information on bank accounts and passwords and increases the utility of returning the product to

$$U_O = \sum_{i=1}^{i=7} \beta_{oij} X_{ij} \quad O \in \{Store,\ Trash,\ Sell,\ Return\} \quad \forall\, j = 1, 2, \ldots, total\ number\ of\ agents \tag{5}$$

manufacturers or even selling it to a third party. On the other hand, since this product loses one of its modules, the buyback price and its second hand market value decreases. In other words consumers have to consider the tradeoff between the monetary benefit and the security issue. *Second hand price* is the product monetary value if the consumer sells it to a third party. Similarly, *buyback price* is the incentive offered by manufacturers if the consumer returns the product. *Buyback* price can be estimated as a linear function of the product's age [47]. The same approach has been applied to calculate the *second hand price* but with one slight difference. The *second hand price* is relatively higher than *buyback* price.

Another factor is the *accessibility* to collection centers which represents how convenient returning the product is. The consumers and the collection centers are randomly distributed in the simulation environment. Therefore, this factor can be calculated based on the average distance to collection centers for each consumer.

Considering the above mentioned factors, the utility of each alternative for every consumer has been calculated based on the linear utility function:

$$U_O = \sum_{i=1}^{i=8} \beta_{oij} X_{ij} \quad O \in \{Store,\ Trash,\ Sell,\ Return\} \quad \forall\, j = 1, 2, \ldots, total\ number\ of\ agents \tag{6}$$

Where, β_{oij} is the corresponding coefficient of attribute i (X_i) for consumer j for option O.

In the second scenario, a different approach has been applied to model the effect of *peer pressure* and *consumer awareness*. Consumers have been categorized into three subgroups based on the degree of their concern about environmental friendly actions: regular consumers and green consumers A & B (Figure 3).

Green consumers generally are more toward green behavior, returning or selling the product rather than storing or trashing them. Green consumers (B) are more environmental friendly in comparison with green consumers (A). *Education level* (X_1), *income* (X_2), product *data security* (X_3), *second hand price* (X_4), *buyback price* (X_5) and *accessibility* (X_6) have been defined in a similar way as previous scenario. In addition, another factor named *environmental friendliness* (X_7) has been defined. Figure 3 presents the consumers states and the immigrations between subgroups.

If the number of returns from a consumer's vicinity reaches a certain level, the consumer is considered as "aware of the return programs" and switches to green consumer (A). Similarly, if the number of returns in the consumer's network of peers reaches a certain level, he will switch to green consumer (B). The value of (X_7) depends on the subgroups: The highest value belongs to green (B) where it decreases for green (A) and regular consumers respectively. In addition to X_7 the coefficients of utility functions are different for consumers in different subgroups. This represents different behaviors of subgroups.

The utility for each option can be found in a similar way as previous scenario:

The ABS model helps cover the current limitations of DCA techniques in two ways: First, through real-time calculation of attribute values, and second, through modeling the impact of choices made by other agents on each individual's choice decision and showing how the utility function of each individual varies depending on the decisions made by other agents. All agents are randomly positioned in the simulation environment, where the accessibility is calculated during runtime. In addition, buyback price and second hand price change over time and their corresponding values differ for each consumer based on the time of decision. So these values cannot be used through regular DCA methods or other simulation techniques ignoring the interaction among agents. Awareness, peer pressure and environmental friendliness are assessed through the interactions of every agent with others and cannot be predicted in advance. Therefore, the current ABS platform aims at expanding the application of DCA techniques to cases in which the choices made by decision maker is influenced by decisions already made by other decision makers and interactions between agents.

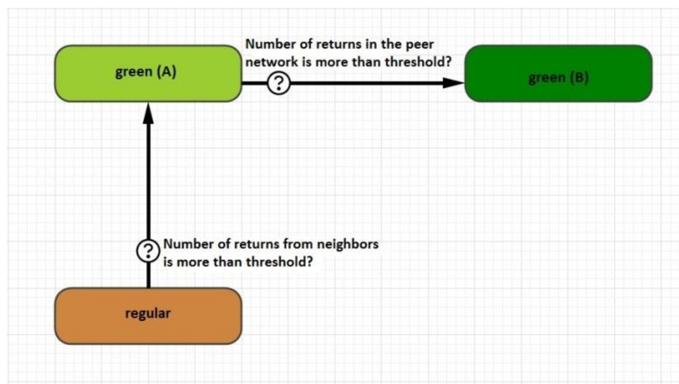

Figure 3. Consumer subgroups

The decision rules of agents are dynamic over time and defined using DCA technique. There are two different dynamic aspects in this simulation. First, the fact that some of the attributes, as described previously, dynamically change over time and since the decision time varies over the consumers the decision process cannot happen in a static fashion. The second aspect refers to the point that network properties of agents (i.e. awareness) are directly connected to other agents' decisions and can change several times during simulation for each consumer.

4. NUMERICAL EXAMPLE

An example of cellphone take back system has been used in this paper to show the application of the model. Table 1 lists the global input parameters of the simulation model. Attribute values and coefficients applied in DCA are summarized in Table 2 and Table 3 respectively.

Table 1. Global simulation parameters

Simulation Parameters	Value
No. of Consumers	500
No. of Cell Phones	500
No. of Collection Centers	3
Ratio of data secured products	0.5
Product Availability Delay	Uniform (0,05)
Usage Time by each consumer	Normal (0.5, 2) years
Simulation Time	1800 days

Table 2. Attributes and their initial values

Attributes	Initial Value	Description
Education level	Uniform discrete distribution (1,4)	
Income	100000*(lognormal(μ=0,σ=1,min=0))	
Accessibility		Calculated during the experiment
Data Security	1 or 0	Calculated based on the probability that "Ratio of the secured products" defines.
Buy Back Price	103-(20.6*(age)-(Data Security)*20)	Changes over time
2ndhandMarket Price	Buy Back Price + 30	Changes over time
Awareness (1st scenario)	-	Calculated during the experiment
Peer Pressure (1st scenario)	-	Calculated during the experiment
Environmental Friendliness (2nd scenario)	-	Calculated during the experiment

Table 3. Coefficients and their value

Attributes / Coefficients	β_{Store} Normal(σ,μ)	β_{Return} Normal(σ,μ)	β_{Trash} Normal(σ,μ)	β_{Sell} Normal(σ,μ)
Education level	(0.25,-0.5)	(0.25,0.5)	(0.25,0.5)	(0.25,0.5)
Income	(0.000002,0.000009)	(0.000002,-0.000005)	(0.000002,0.00002)	(0.000002,-0.000005)
Accessibility	(0.001,0.02)	(0.002,-0.004)	(0.001,0.002)	(0.001,0.002)
Data Security	(.5,-1)	(.5,2)	(.25,1)	(.5,1.5)
Buy Back Price	(0.01,-0.02)	(0.01,0.06)	(0.01,-0.04)	(0.02,0.02)
2ndhand Market Price	(0.01,-0.02)	(0.02,0.02)	(0.01,-0.02)	(0.01,0.035)
Awareness (1st scenario)	(1,-3)	(1, 3)	(1,-3)	(1,-3)
Peer Pressure (1st scenario)	(1,-3)	(1, 3)	(1,-3)	(1,-3)
Environmental Friendliness (2nd scenario)	(0.05,-1)	(0.05,1)	(0.05,-1)	(0.05,0.4)

Before explaining the numerical example, there are several points which should be noted:

1- The coefficient values are selected such that after multiplication in the corresponding attribute the values become comparable. However in reality this is not always true since one or several of these attributes can have significant effect or no effect at all. We have tried to select the attributes which have been shown in the literature to have significant effect but the exact information on the scale of coefficients should be assessed true real survey data analysis.

2- The numerical example provided in this section is to verify the simulation model. As long as the results are in line with the assumptions, the model functionality is verified. However, the actual validation of the model can be done using real subject data. It should be noted that the survey analysis is beyond the scope of this work and the main contribution of this study is to build the ABS platform. Validation of the model results using real subject data and the calibration of coefficients using econometric techniques on survey data are among our future studies.

In order to investigate the impact of interactions between agents we need to define an index to quantify the agent interactions. We presented two different scenarios to define peer pressure and awareness in order to magnify the effect of consumer interactions.

The difference between the two proposed scenarios is in the consideration of consumer interactions and their environmental concerns. The first scenario utilizes *peer pressure* and *awareness* to show the effect of agent connections on their environmental awareness. However, in the second scenario *environmental friendliness* index has been used directly. In the latter case, other agents' decisions change the state of the consumer from a regular consumer to a green one.

4.1 Scenario I: All consumers have similar environmental concern

In order to show the impact of consumers' interactions on their choice decision, two different cases have been studied under each scenario. In the first case, the simulation is run without considering the effect of *peer pressure* and *awareness*. Therefore, consumer decisions only depend on their socio-demographic characteristics and product design features. In the second case, the effect of consumer interactions has been considered using peer pressure and consumer awareness factors. Figure 4 illustrates the trend of each option for the first case and Figure 5 shows this trend for the second case where consumers interact with each other.

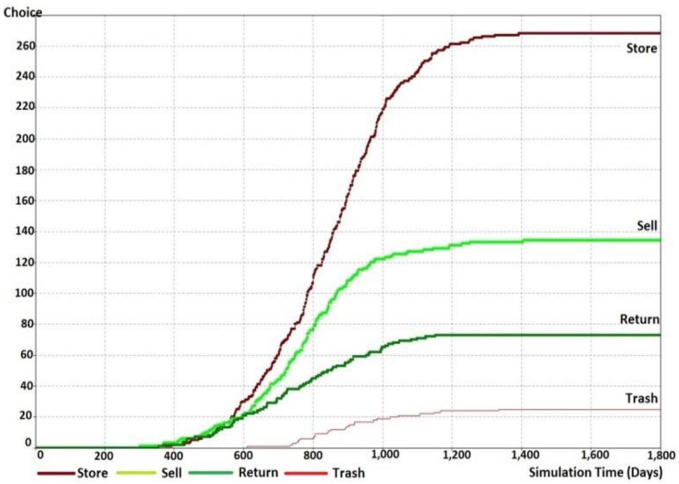

Figure 4. Scenario I, Case I: number of products stored, returned, sold and thrown away over time. No consideration of interactions between consumers

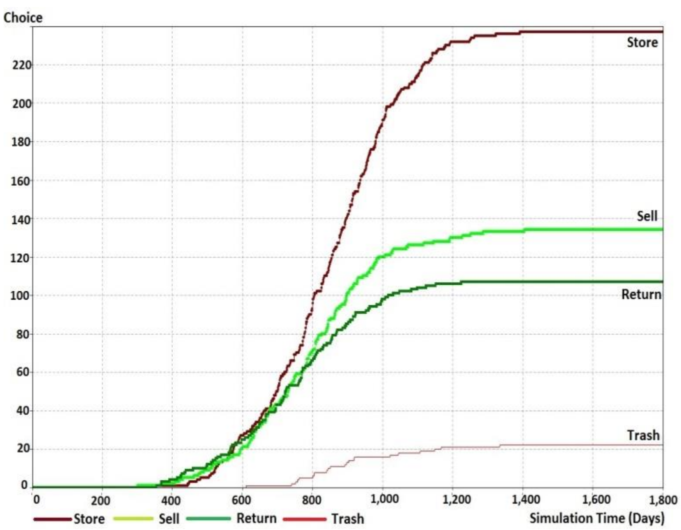

Figure 5. Scenario I, Case II: number of products stored, returned, sold and thrown away over time. With consideration of interactions between consumers

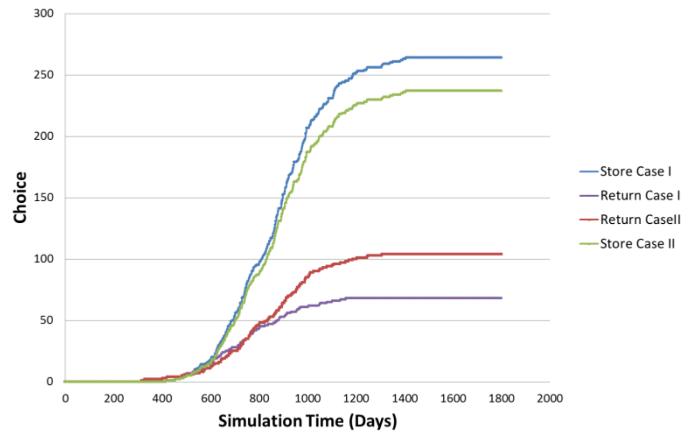

Figure 6. Comparison of results for Scenario I

As shown in Figure 4, there is an almost 300 day delay before any outcome is observed. This is expected due to the time needed for products to become available in the market in addition to the usage period. Moreover, since the buyback price and second hand market value have negative correlation with product age, their positive effect on returning or selling is more dominant at the early stage of simulation.

In other words, if a consumer stops using a product earlier, there is a higher chance that he decides to return or sell it. The slope of return and sell curves are larger compared to store at the beginning of simulation, however they decrease relatively to store over time. The curves become stable after 1400 days so that 54% of the products end up in storage. 14% of the consumers return their product, 27% sell their product and 5% of the products end up in trash.

Figure 5 illustrates the effect of interactions between consumers. As seen, consideration of peer pressure and awareness has a positive effect on the return decisions. In this case, 47% of products end up in storage, 21% of them will be returned, 27% will be sold and 5% end up in trash. This confirms our proposition regarding the positive effect of consumer interactions on increasing the return rate.

Figure 6 compares the highest changes for two cases in scenario one. As can be seen with consideration of interactions Trash and Sell almost remain unchanged however the values of Return and Store changes.

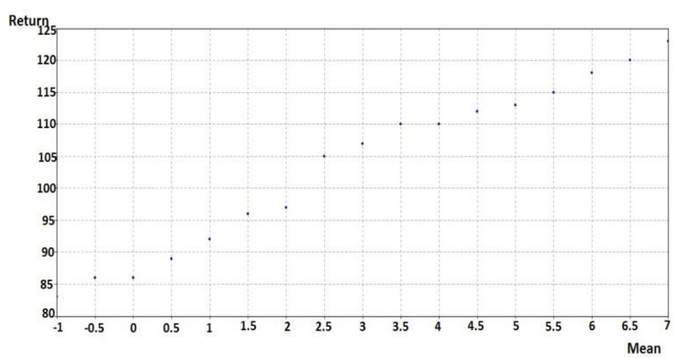

Figure 7. Sensitivity analysis of the impact of awareness (mean value of β) on the number of returns

A sensitivity analysis has been done to further investigate the effect of *peer pressure* and *awareness* on the output of the simulation. The values associated with the coefficients (β) denote the weight of effectiveness of each factor. These values are summarized in Table 3. For *awareness* and *peer pressure* the coefficients have been extracted from a normal distribution. The sensitivity analysis has been done on the mean value for the corresponding coefficients. The mean values change from -1 to 7 with steps as large as 0.5. Figure 7 and Figure 8 show the effect of changing the mean on the number of returns for *awareness* and *peer pressure* respectively. For each case the other factor is kept fixed at (μ=3). If μ increases the normal distribution produces larger values and the factor becomes more dominant. Thus, since these two factors have a positive effect on the utility derived for return, increasing them will increase the number of products which will be returned at the end of the simulation (Figures 7, 8).

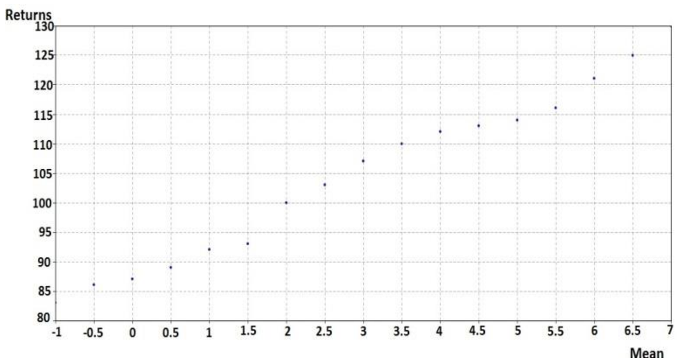

Figure 8. Sensitivity analysis of the impact of peer pressure (mean value of β) on the number of returns

4.2. Scenario II: Consumers are categorized in three groups based on the level of their environmental concern

Similar to previous section, two cases have been studied within the second scenario in order to investigate the effects of consumer interactions.

Figures 9 and 10 present the simulation results for two cases of the second scenario. The observed behavior is similar to previous case except that the interactions have a greater impact. While in the first case a total of 51 products have been returned at the end of the simulation (1800 days), the effect of subgroups and immigration of consumers between them has increased this value to 129 in the second case.

As mentioned above, with current configuration of the attributes and coefficients the two scenarios have similar functionalities. However, considering different states for environmental concerns of each individual has impacted the results of the simulation in a larger scale.

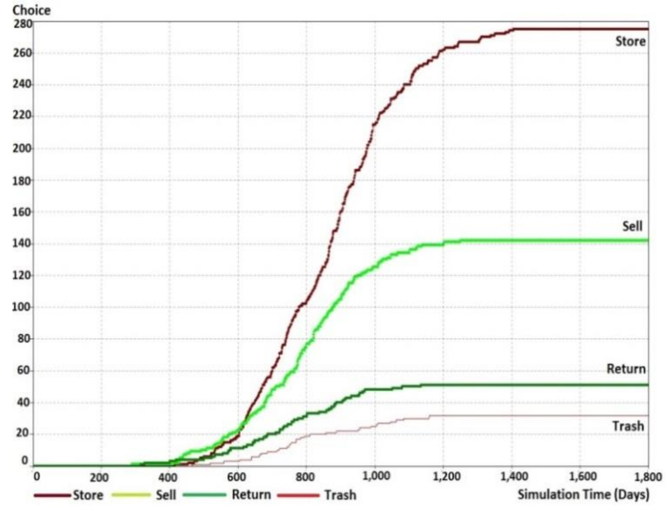

Figure 9. Scenario II, Case I: number of products stored, returned, sold and thrown away over time. No consideration of interactions between consumers.

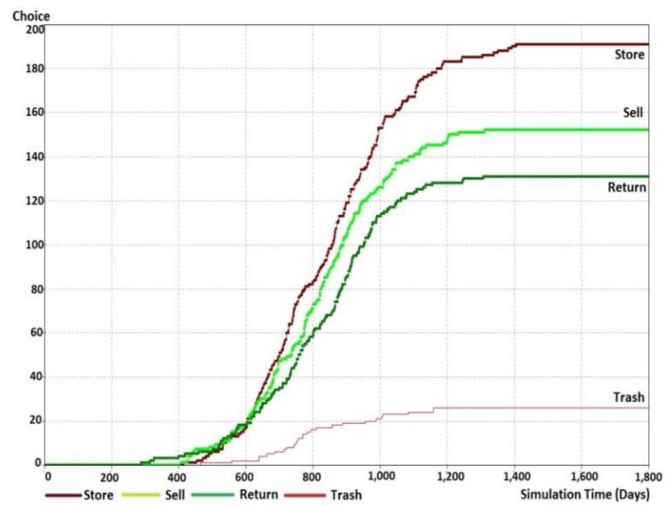

Figure 10. Scenario II, Case II: number of products stored, returned, sold and thrown away over time. With consideration of interactions between consumers

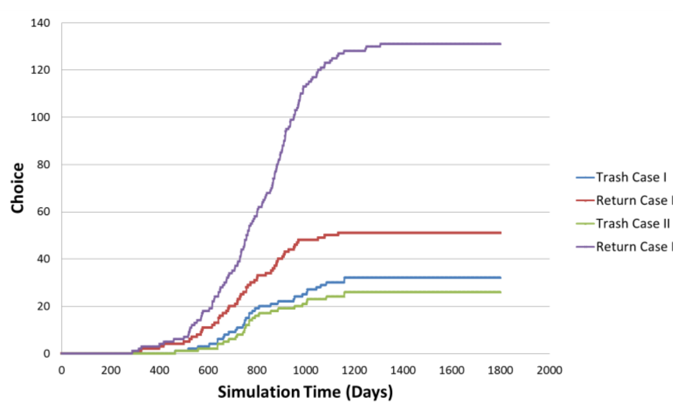

Figure 11. Comparison of results for Scenario II

Similar to Figure 6, Figure 11 compares the changes for two cases in Scenario II. However in order to show the scale of the changes Figure 6 illustrates the highest change (Return) and the lowest change (Trash).

4.3. Impact of design features on the number of returns

A cellphone design in which consumer can detach the memory from the whole module is considered in this section. This feature has a positive impact on the data security concern and a negative effect on the buyback price in the utility function. From the manufacturer's perspective, it is important to know what portion of the products should be manufactured with this design and how it affects the return behavior.

In order to investigate the effect of proposed design on return decision, a sensitivity analysis has been done on the effect of the ratio of secured products on the number of returns. It should be noted that for each attribute in the utility function the corresponding coefficient also plays a big role on the magnitude of that attribute effect. These coefficients commonly are found from survey analysis studies. Finding the real betas is beyond the scope of this paper. However we considered three different sets of coefficients for *buyback price* and *data security* to show the behavior of the system under different circumstances. We considered three different mean values for β_{Return} for *buyback price* (μ= 0.02, 0.06 and 0.1). The rest of the parameters are the same as Tables 1 to 3 and we followed the second scenario for the consideration of consumer interactions.

Figures 12-14 show the results of the analysis. In Figure 12 the coefficient for buyback price is relatively small, therefore the effect of data security is dominant and increasing the ratio of products with this design increases the total number of returns.

In the second case (Figure 13), as the coefficient for buyback price increases the total number of returns will increase. However, the tradeoff between buyback price and data security keeps the number of returns constant for different ratios. Figure 14 presents the case that buyback price has dominant effect on the number of returns. Total number of returns increases drastically at first but as the ratio increases, the number of returns will decrease as it cancels the effect of buyback price.

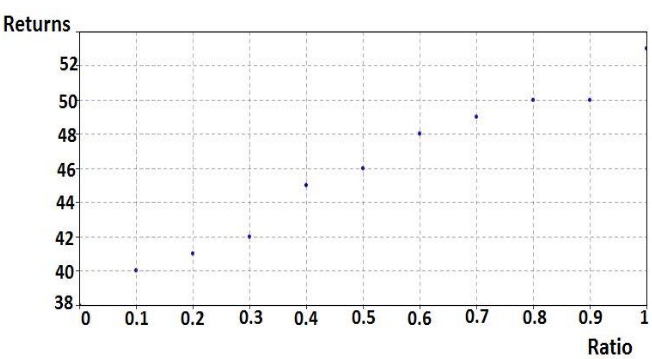

Figure 12. Number of Returns vs Ratio of products with data security feature (μ= 0.02)

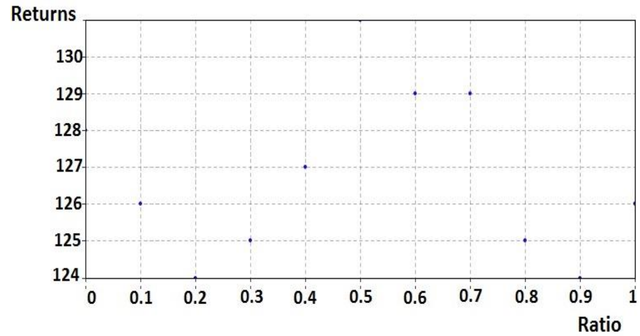

Figure 13. Number of Returns vs Ratio of products with data security feature (μ= 0.06)

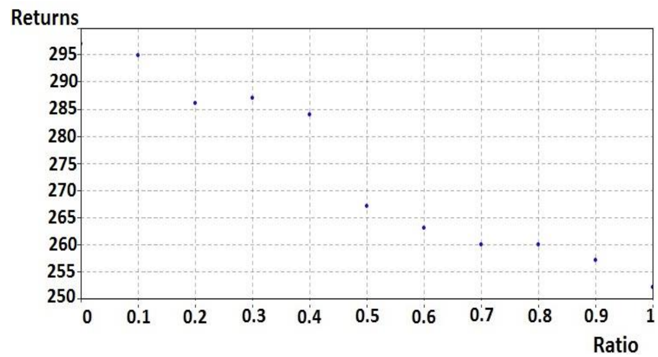

Figure 14 – Number of Returns vs Ratio of products with data security feature (μ= 0.1)

5. CONCLUSION AND FUTURE WORK

Understanding consumer decisions on returning used items and the factors affecting this decision is of great importance to manufacturers and policy makers. This paper integrated agent based simulation model and discrete choice analysis to study consumer decisions regarding used products. Product design features and consumers socio-demographic information have been included in the model as factors affecting consumer choices. The interaction between agents has been modeled using the capabilities of ABM. A numerical example of cellphone take back system is used to show the application of the model.

This work can be enriched by calibrating simulation results using real survey data. The coefficients in the utility functions are based on assumptions. However the results of the model will be more reliable if the coefficients are extracted from real consumer attitudes using survey analysis methods. Validation of the model requires real data on the consumers' return behavior such as EPA reports. Moreover, survey data are needed to calibrate the attributes and their weight coefficients. Conducting a survey analysis study on people's real return choices, their socio-demographic information and their interactions with their peers, neighbors and relatives is the major base line for future work.

In addition to survey data, social network data are helpful in quantifying the performance of consumers' interaction considered in this study.

Product design attributes such as detachable memory and security feature have been studied as an example since less attention has been paid to them in the literature, although they may have considerable impact on the return behavior of consumers. Current designs ignore the end-of-life impact of detachable memory in favor of other features such as packed design, size, and less weight.

More design features such as product family generation, technical obsolesces, software version, and usability of operational systems can be considered in future studies.

Loss aversion was introduced as one of the possible influencing factors in Section 2 and it can have pivotal effect in decision making process. Considering loss aversion and converting the utility functions into reference dependent utility concept can also improve the precision of the study.

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