A MULTIAGENT FRAMEWORK FOR CONSUMER BEHAVIOR AND PURCHASE INTENTIONS IN ELECTRONIC COMMERCE

By

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ABSTRACT

An agent based model (ABM) to investigate the dynamics of human purchasing behavior within an online environment is presented. Based on empirical research, both extrinsic and intrinsic influencing factors such as disposition to trust, impulsive behavior, security perception and others were identified to describe the characteristics of a population comprised mainly of college students. Classification tree analysis was used to generate the decision rules and parameters serving as input data for the model. As a result, this study demonstrates how ABM can be used to analyze consumer behavior to cope with the dynamic changes and complexities in a real-world environment. Experimental findings suggest that the adaptation process to this environment is mainly based on both the increment on the level of trust in online review sites visited, along with an increment in the knowledge about the procedures and security mechanisms available for online transactions. Both factors reduce the rate of non-buyers.

RESUMEN

Esta investigación presenta el desarrollo de un modelo basado en agentes (ABM) para investigar la dinámica del comportamiento humano en las transacciones va internet. Basado en un estudio empírico se identificaron factores internos y externos tales como la disposición a la confianza, el comportamiento impulsivo, la percepción de seguridad entre otros; los cuales, describen las características de una población compuesta mayoritariamente por estudiantes universitarios. Se utilizo una técnica de minería de datos para generar las reglas de comportamiento y los parámetros que sirvieron de entrada al modelo. Como resultado, se muestra la utilización de un ABM para analizar el comportamiento del consumidor y manejar los cambios dinámicos y complejos de un entorno real. Los resultados sugieren que el proceso de adaptación a este medio se basa principalmente en el incremento del grado de confianza en las revisiones presentadas en un sitio web conjuntamente con el incremento en el conocimiento sobre los procedimientos y mecanismos de seguridad ofrecidos para realizar transacciones en línea, los cuales, reducen la tasa de no-compradores.

To God, guide and support of my life. Because everything in Your hands turns good

To my wife, my best friend and complement of my life. Because this achievement is yours as well

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LIST OF ABBREVIATIONS

ABM	Agent Based Model.
CHAID	CHi-squared Automatic Interaction Detector.
TAM	Technology Acceptance Model.
MAS	Multi-Agent Simulation.
KMO	Kaiser-Maier-Olkin.

CHAPTER 1
INTRODUCTION

1.1 Introduction

Nowadays, we live in a society characterized by information and knowledge. This type of society leads to a profound and continuous change in citizens behavior. There are two major factors giving rise to this change: the technology revolution and globalization of the economy. The first one was consolidated in the early years of the last century, and was defined as the “digital revolution” that involves the processing of information in binary codes that can be easily transmitted. Such innovations have a direct impact on the economy, and its rapid development leads to its rapid incorporation into business activities. This new economy is giving rise to a feeling of uncertainty due to changes in new business models that are replacing traditional ones.

Online transactions constitute now a significant part of commercial activity. For example, in the case of Puerto Rico, a study developed in 2007, stated that online shopping grew in 29% wih respect to the year 2005 and in 15% with respect to the year 2006. This report, presented by Visa and developed by the Society of American Business Intelligence, also showed that Puertorricans spent around $445 millions in 2007 making online purchases. The study also suggests that this growth is due to advances in technology and increased use of credit cards [1].

The increasing prevalence of the internet, coupled with the efficiency and convenience of online transactions is likely to change both consumer behavior and business practices [2]. Although the commercial potential of this environment has encouraged researchers to focus on studying consumer behavior with respect to online transactions, however, this field is still in an exploratory stage [3]. Some of the basic premises, such as the quality-satisfaction-loyalty relationship, that underlie offline transactions apply to online environments. However, due to the nature of the virtual interface of a web site, i.e. there is no visual interaction between the customer and the seller; there is also a change in expected behavior when reacting to this interface. In the literature, there are theoretical models that capture the main characteristics of the interface and explain how the user reaction to the interface, determined by a derived set of user characteristics, moderates consequent behavior [4].

One of the largest challenges in the growing of electronic commerce is the lack of trust and security consumers' feel while dealing in this enviroment. Two of the factors that make consumers feel insecure when making online transactions are to provide personal and financial information online [2]. This mistrust should be reduced in order to increase consumers' online purchase intentions. Bahmanziari [2], suggest that a low level risk is a key factor in potential online consumers purchase decisions. Those concerns are often addressed through the use of assurance structures placed on the web site. The effect of assurance structures may moderate customer's decisions and induce more trust and purchase intentions and ultimately, behavior.

In this thesis, the online environment could be seen as a complex system in which entities (consumers) may have a dynamic behavior, i.e. interact with each other and change their decisions over time based on that interactions. This interaction influences entities behavior and thereby generates an emergent phenomena within the system.

1.2 Research Objectives

Despite the strong growth of online transactions, many challenges remain in the practice of electronic commerce. These challenges include increasing the low conversion rate of visitors into buyers, reducing the abandonment of electronic shopping carts and decreasing the lack of trust consumers have in online transactions. Therefore, to pretend achieving those challenges, research is needed to understand the drivers for consumer behavior and the dynamic nature of the online environment.

For this purpose, the main objective of this research has been defined as to:

- Analize the dynamics of human behavior in the execution of commercial activities in an electronic commerce environment.

The following secondary objectives were also defined for assisting in achieving the main objective:

- Identify extrinsic and intrinsic factors influencing online consumer behavior and purchasing intention. Those factors involve personality determinants of online shopping and consumer's socio-economic characteristics.
- Develop a prediction model for exploring consumer behavior in e-commerce. This model helps in determining the decision rules to predict future behavior in online purchases. Also the decision rules will allow us to classify consumers in different groups each representing a particular behavior that follows a set of rules with certain likelihood.
- Develop an Agent Based Model as a framework to represent consumer online behavior. This model not only represent the behavior of individual consumers, but also represents the interaction process between consumers which is a natural form for transmiting information, experiences and also knowledge. This model could be then used to evaluate how the interaction affects the resulting collective behavior.

The interest in analyzing the dynamic behavior in virtual stores has been growing. Indeed, Richard and Chandra [5] discussed the impact of environment on the consumer behavior through the application of experimental techniques centered in online purchase environments.

We decided to approach this research towards the analysis of consumer behavior and the influence that several factors have on consumers' purchase intentions. Thus, we intend that our research will lead us to offer potentially interesting answers regarding the feeling of satisfaction or dissatisfaction consumers have during the purchasing process, the perception of risk in the virtual environment during the act of buying, the disposition to trust in electronic transactions and so on. Ultimately, all analyze environmental and personality traits that affect significantly the consumer behavior and are particularly relevant for developing merchandising strategies in retail establishments operating in the web.

This research also presents the development of an agent based model to analyze the dynamics of human behavior in the execution of commercial activities within an e-commerce environment. We aim that our research will lead us to offer potentially interesting answers regarding triggers of consumers' satisfaction or dissatisfaction that influence their decision to buy. As a result, the model shows how agent-based simulation can be used to study consumer behavior to cope with the dynamic changes and complexities in a real-world business environment.

To capture consumer's behavior and purchase intentions, many factors should be used. Those factors involve personality determinants of online shopping that may influence impulse purchasing behavior during online transactions. Other factors are going to be considered such as web site characteristics (i.e. electronic commerce interface), and customer's social characteristics that may influence over on-line customer's purchase intentions.

1.3 Research Scope

This research is aimed in investigating the characteristics of a particular segment of the consumer population, in this case represented mostly by college students from the University of Puerto Rico at Mayagüez. A feature of this population is that they tend to spend considerable time on internet and make use of technology to conduct most of their daily activities.

This young population seems to be an emerging and wealthy market of potential customers. Therefore, it can be seen as an attractive segment for companies considering expanding into the online market. Moreover, this is a generation that seeks change and feels comfortable with technology.

Another reason for why we have chosen this segment in particular is that there is very little research about this generation of buyers ([6] and [7]). A profile of the behavior of such clients would have great value in planning the marketing strategy to attract this segment.

1.4 Contribution of this Research

Different from previous studies which focus on the consumer decision process, we have developed a model that integrates consumer personality, sociology and economics, which is to treat the consumer decision process as the process of how the consumer intention has been formed. The simulation model has been done based on social, economic and psycological characteristics of consumer behavior.

Given that consumers can change their behavior over time, interact with other consumers and generate an emerging collective behavior, a multi-agent framework that represents consumer behavior and purchase intentions in an electronic environment is a useful tool to represent this kind of dynamic behavior.

Since e-commerce environment provides a dynamic behavior of consumers and moreover e-commerce is known to be a complex system we decided to use the advantages of the Agent Based Model (ABM) for attacking the problem previously defined.

By using agent based modeling, which is a highly recommended tool specially in cases where the systems being modeled contain active objects such as people ([8], [9], [10], [11], [12], [13]), we are able to simulate the simultaneous operations of multiple agents, in this case consumers, in an attempt to re-create and predict the actions of complex phenomena.

Moreover an Agent Based Model has the capacity to represent the emergent behavior of a system which is an important role in developing and analyzing theory models of interactivity in human societies [11].

Prior to the conception of ABM, modelling economic markets relied on the notion of homogeneous agents and make the problem to be analytically and computationally tractable. With ABM we are able to take a more realistic view of this system since it represents individual behavior following their own rules.

To mimic a real-life consumer, the beliefs, knowledge, and objectives of the consumers are captured using classification tree analysis. In the simplest form these behavioural patterns can be represented in an ABM by rules of decision which describe what an agent will do under certain circumstances. Interactions between agents were also captured, as these are central to the communicaton of information through the system and can lead to modification of the behavior of the consumers. For example, as word of mouth is important for a consumer undertaking a decision to purchase online then classification tree analysis provides with the behavioral rules that determine the likelihood of a consumer to be influenced by other consumers or by the reviews presentd on the web site.

Another strength of this methodology is that the Multi-agent Based Simulation is governed by certain rules of decision based on an empirical study which generates a more realistic approach for modelling and understand consumer behavior within the population studied. It also allows to incorporate details in the decision processes experienced by the consumers and the configuration of the social network to be incorporated explicitly.

This research will provide a multi-agent framework exploring the impact and dynamics of the consumer behavior engaged in online shopping. It also serves to examine the level of interactivity with the web site which is critical in getting web site visitors involved in the transaction process. And finally, this tool will help to find whether the identified factors affect positively in the purchase behavior of online consumers.

1.5 Organization of this document

Our interest in achieving the different objectives outlined above, leads us to the need of conducting an analysis and an assessment of both theoretical and empirical effects. Those effects refer to the influence of the virtual environment toward consumer behavior. The content of this research is divided into six chapters, being the first one the introductory section. The second one describes the literature review, following by the third chapter that conducts the development of empirical contents. The fourth chapter covers the design of the multi-agent model and finally the fifth chapter outlines research findings and conclusions.

The second chapter, which forms the theoretical framework of this research, is divided into two sections. In the first section, we discuss the main aspects that characterize the e-commerce from the perspective of consumers, especially in deepening the analysis of their purchasing behavior over the Internet as a means of virtual interaction. To do this, we first talk about the definition and importance of electronic commerce as well as factors behind the adoption of the Internet as a new sales channel. Then, there is an analysis of the consumer motivation for buying and the satisfaction gained through this experience. Next, we come to analyze the main work carried out by researchers who have worked these issues and have given rise to certain patterns of behavior, of which we have used for the development of our empirical analysis. Finally this section outlines the major differences between online and offline behavior in order to get a clear vision and distinctive trend of our research.

In the next section we will approach the study of modeling through agents, its principles, characteristics and applications of this technique. Also, we will discuss the use of agent based modeling to simulate emergent behaviors in social sciences, particularly within the atmosphere of shopping online.

In the third chapter, we describe the methodology and research design, which incorporates the empirical analysis, beginning from the procedure for collecting information, the sample selection and the process of constructing the questionnaire. The second part of this chapter specified the procedure and the technical analysis of the data collected. We used factor analysis to ensure that constructs previously defined in the literature hold for this population and that the questionnaire measured the appropriate variables. This analysis of consumer behavior reveals certain predictors that may contribute to analyze the perceptions, attitudes and preferences of consumers and their buying behavior to get a full understanding of their online needs.

Chapter four describes the prediction model for exploring consumer behavior in e-commerce generated using classification tree analysis. We used CHAID as a learning system to derive the decision rules from existing data in order to find significant patterns to profile consumers. The aim of this chapter was to determine decision rules to predict future behavior in online purchases. Also, these decision rules will allow us to classify customers in different groups each presenting a particular behavior that will follow a set of rules with certain likelihood.

Chapter five explains the development of the multi-agent based model in detail. The chapter describes the development of the agent-based simulation, which is based on consumer profiles found previously. After that, Chapter five describes the algorithms, rules of decision and the rules of interaction that control agent's behaviors.

In chapter six, we present the results and findings obtained in this research. This chapter focuses on a detailed analysis by developing an experiment to study the effects of subjecting the simulation runs to different parameters. Those parameters represents different levels of the variables that were found to be the most influential in consumer behavior for the population studied.

To conclude this research, we will expose the principal conclusions arising from the implementation of our methodology based on the gathered information. This research concludes with the declaration of recommendations for future investigations that we thought would be interesting to continue.

CHAPTER 2
LITERATURE REVIEW

First, it is necessary to discuss about previous studies on consumer behavior and purchase intentions either by traditional means or by virtual stores. This will help us to assess the factors influencing consumer behavior and promote changes in their purchase intentions.

In the case of online purchases, we offer a literature review of the factors that induce consumers to buy through this medium. In addition, it is intended to answer the question about the factors that make consumer rely to make purchases through a website. Also we want to identify the factors that make consumers feel attracted to review the products offered in the website, creating changes in their behavior and in their purchase intentions.

Next, we present the fundamental concepts of an agent-based model (ABM). It is useful to understand what an ABM is, the contributions, the pros and cons of this tool, how it is useful to make simulations, etc. This section then describes the appropriate environments in which it is recommendable the use of ABM. It is also important to know about previous investigations in ABM and the application areas in which ABM is currently used.

Finally, we present some research applications using ABM to simulate consumer behavior in different areas.

2.1 Consumer and purchase behavior

Consumer behavior attempts to understand the buyer decision making process, both individually and in groups. It studies characteristics of individual consumers such as demographics, psychographics, and behavioral variables in an attempt to understand what people pursue. It also tries to assess the influences received from groups such as family, friends, reference groups, and society in general.

The buying decision process model (Figure 2–1), is a widely used tool for marketers to gain a better understanding about their consumers and their behavior. The idea of this model resides on five steps. When a customer purchases an item, the purchase event is a forward-moving process, which begins long before the actual purchase and continues even after the purchase is made. Comegys et al. [7], found that there is a positive relationship between the purchase process stages and the increase in purchase volume.

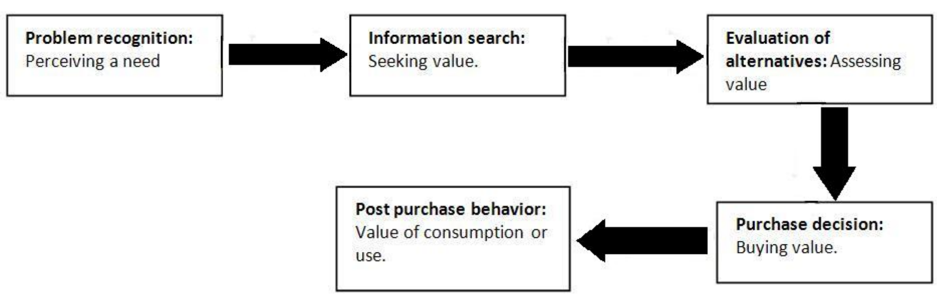

Figure 2–1: The buying decision process. Adapted from Comegys et al. (2006) [7]

2.1.1 Consumer profile in a virtual environment

There are an important number of studies that classified consumers who realize online purchases ([14], [15] and [16]). Lorenzo [14] called this type of consumers as virtual consumers.

The principal intention of this classification centers on identifying groups of virtual customers as more related as possible to generate strategies that allow to adjust to his/her profile. In this sense, Harris Interactive [15] categorizes the virtual customers according to the satisfaction obtained after virtual purchases. Each of which having a distinct profile helping in explaining online shopping motivations and predicts future shopping behaviors. The study of [15] contains more than 3,000 respondents and also shows that the size of these groups has changed over time, implying that as e-commerce evolves, the population of shopping types and their behaviors can be expected to change as well. The six types of shoppers and their respective percentages of the total cyber shopping population are defined as follows; the six types are listed in order of their ratings of "overall satisfaction with the online shopping experience," from least satisfied to most satisfied:

1. E-bivalent Newbies (5%): Newest to the Internet, this population is somewhat older, likes online shopping the least among the six types, and spends the least amount online.
2. Time-Sensitive Materialists(17%): This group is most interested in saving time and maximizing convenience, is less likely to read product reviews, compare prices or use coupons.
3. Clicks & Mortar (23%): These individuals tend to shop online but prefer to buy offline, are more likely to be female homemakers, have privacy and security concerns about buying online, and visit brick-and-mortar shopping malls most frequently.
4. Hooked, Online & Single (16%): Members of this group are more likely to be young, single males with high incomes, have been on the Internet the longest, play games, download software, bank, invest and shop online the most often.
5. Hunter-Gatherers (20%): More likely to be married, this group is typically age 30-49 with two children, most often goes to sites that provide analysis and comparisons of products and prices.

6. Brand Loyalists (19%): These people are the most likely to go directly to the site address of a merchant they know, are the most satisfied with shopping online, and spend the most online.

Virtual customers were classified depending on his/her principal uses and motivations to use the Internet. Mckinsey and Media Metrix [16], one of the leaders in internet and digital media audience measurement, analyzed online behavior using a sample of the most active online customer among the Media Metric U.S panel of 50,000 people under measurement. They obtained six segments of online users:

- Simplifiers (29% of active users), use the internet to make their life easier and require superior "end to end" convenience.
- Surfers (8% of active users), people who spend the most time online and use the internet for a wide range of purpose, among them buying products.
- Bargain (8% of active users), like to find the best buys online and use the internet for a combination of shopping and entertainment as they find deals.
- Connectors (36% of active users), are internet newcomers, use the internet to connect and communicate, and are more strongly tied to offline brands.
- Routiners (15% of active users), use the internet as a regular source of information and are not necessary online shoppers.
- Sportsters (4% of active users), use the internet for information, like the Routiners, but focus their search in on sports and entertainment sites.

The adoption of the diverse types of consumers to this new sale channel does not take place at the same time, or in the same way. A learning curve exists for each type of customer that changes depending on his/her characteristics and a diverse number of external factors that change his/her behavior [17]. For such reason, we exhibit diverse conceptual models that talk about the factors concerning on consumer behavior.

2.1.2 Consumer behavior models

There is a considerable amount of research on online consumer behavior that has focused on understanding the coupling of the quality-satisfaction-loyalty of a website. Prior investigations show that satisfaction with the website is decisive in the outcome of the behavior and attitude of the consumers. This relationship is subject to various consumer's characteristics such as their preparation with regard to technology used, motivations for the purchase, demographics, trust and risk. In an online context, it is important, especially when consumers visit or perform a transaction on a website for the first time. A major challenge for businesses online is therefore to suggest what factors are affecting the relationship between consumer satisfaction and the website [18]. The study and representation of those factors will provide information about the interaction between the customer and the web site.

Generally, consumer's confidence in the initial transaction is quite low. Some web sites try to gain confidence from published testimonies of others who already made transactions on the website. However, not all customers rely on the testimony of others, even for those willing to take the risk to accept. Rather, consumer's confidence, given the level of awareness of the product or service provider, is likely to be the dominant determinant of the propensity to make purchases during the initial transaction [19].

Li and Zhang [17], present a conceptual model that shows the factors influencing online purchase behavior. As diagrammed in (Figure 2–2), the number of online purchases and the frequency consumers buy online is dependent to certain degree on their channel knowledge and perception of channel utilities. Consumer's online buying behavior also is affected by two shopping orientations. In that model, we can see that a convenience orientation will have a positive impact, whereas an experiential orientation will have a negative impact. Gender, income and education will affect the level of channel knowledge and indirectly influence online buying behavior.

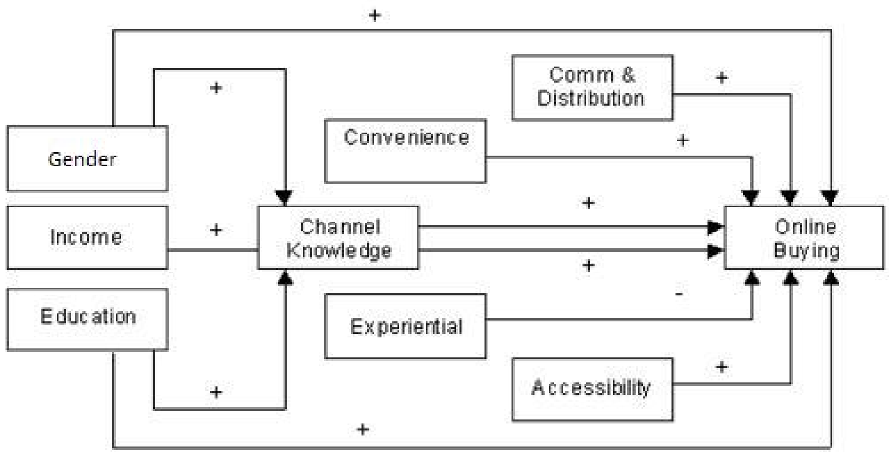

Figure 2–2: A Conceptual model on consumer online buying behavior. Adapted from Li and Zhang (2002) [17]

The actual use of the Web as a shopping channel not only requires certain resources, but also requires knowledge about the Web or "Internet literacy." Consumers undergo a learning curve in adopting the new channel, and the shape of the curve may be different for different types of consumers [17]. One would expect that consumers with different levels of channel knowledge tend to feel differently about using the Internet for shopping and buying purposes. The conceptual model developed by [17] (Figure 2–2), shows that a consumer with more knowledge of the Web is more likely to have a positive perception of the channel utilities, which, in turn, will have a positive impact on actual online purchases. As a conclusion, channel knowledge also may affect the frequency of online purchases.

In an online context, the interaction with the client is a non-personal interaction. According this view, the customer satisfaction is driven by the characteristics of the web site in addition to the characteristics of the product or service associated with it. Therefore, the characteristics of the web site are determinants of customer satisfaction, potentially lead to favorable results for the business. Another factor that increases confidence in customers is the transaction security of a website which in turn increases customer satisfaction. As customers begin to have confidence, the uncertainty generated is also diminished which lowers the risk of the transaction.

In addition to web site characteristics, there are also personality human factors that determine the willingness to purchase products online. Bosnjak et al. [20], develop a hierarchical model of personality useful for predicting consumer intentions to purchase products and services online.

In doing so Bosnjak et al. [20], provide an overview of the determinants of online shopping (Figure 2–3). One factor that influence consumer behavior to buy online is that consumers prefer the mode of buying that has the best ratio of search costs (i.e. time needed to find the best product for the lowest price) and the expected benefits of making a decision. Another approach is that socio-demographic characteristics of potential consumers are also determinants of online shopping behavior. These characteristics refer to the life style of customers, i.e. their way of life and patterns of spending time and money. Besides those relatively easily observable behaviors, most lifestyle typologies also include internal factors, such as buying motives and needs, interests, values, and opinions.

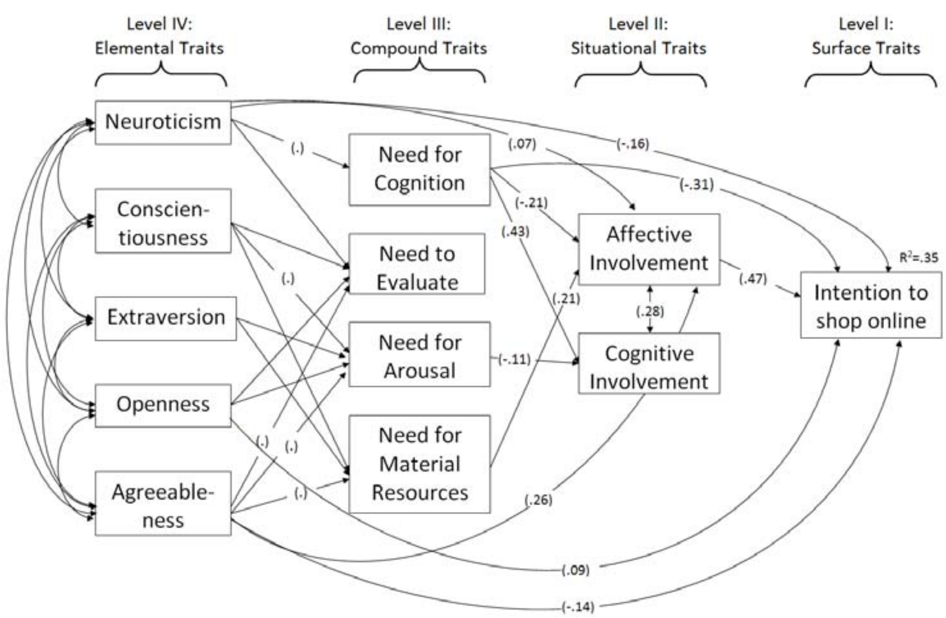

Figure 2–3: Hierarchical model to predict and explain the willingness to shop online with standardized path coefficients. Adapted from Bosnjak et al. (2006) [20]

According to this model, willingness to buy online could be summarized as follows: the higher one's affective involvement, the lower one's enjoyment in cognitively demanding tasks (need for cognition), the higher one's emotional instability (Neuroticism), the lower one's agreeableness, and the more open one is for new experiences, the higher is one's willingness to buy products and services online.

Cognitive Involvement does not appear to be a significant determinant of online buying intention. Instead, the only item of involvement that predicts buying intentions is Affective Involvement. There is a direct arrow from the Need for Cognition (level III), as well as from several traits at level IV, to the willingness to buy online (level I). Finally, these data indicate that "Need to Evaluate" has neither a significant direct nor mediated effect on the willingness for online shopping.

At this point, we can assert that in an online environment web site characteristics and customer personality determines how their behavior will be when making an online transaction and therefore, how this behavior will change in every stage of the buying decision process. Comegys et al. [7] investigate the online purchase behavior of a segment of the population that they call "The Net Generation". This population is represented by university-aged student from two of the world's most advanced Information Technology nations with the greatest potential in e-commerce: Finland and the USA. Information about online shopping behavior in 2002 was compared with information in 2004/2005 for the two countries. They found that for the "Net Generation" there is a positive relation between internet usage and online purchases volume. For both countries analyzed people with high internet usage tends to buy more from internet.

Jahng et al. [21] categorized consumers with respect to the following variables: skill level in technology, risk sensitivity, disposition of trust and demographic criteria (gender, age, family status, level of education, and area residence), which will have a significant effect on the relationship between satisfaction and website behavior and attitude of consumer's subsequences (Figure 2–4).

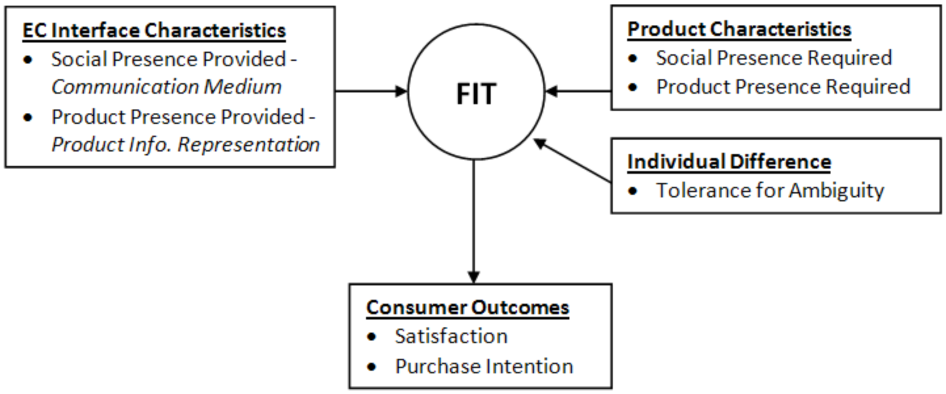

Figure 2–4: Relationship between satisfaction and website behavior. Adapted from Jahng et al. (2006) [21]

Alternatively, when a customer already has an intention to purchase, it is necessary to evaluate the purchase behavior at this time. Zhang et al.[4], tested and identified the factors that influence a customer to purchase impulsively when making online transactions (Figure 2–5). They define impulsive purchases to those unplanned purchases that occur whenever customers experience a sudden urge to buy something unplanned immediately. In the case of traditional shopping, it is the salesperson or cashier who can be the stimulating factor when making a purchase, or promoting products that may influence an impulsive purchase behavior. This feature has been widely studied and used by the marketing techniques, just to ensure that buyers have an impulsive behavior.

The question Zhang et al. [4] want to respond is whether there is a relationship between factors such as gender, subjective norms, impulsive nature of the buyer and intent to buy. Their results show how these factors influence the behavior of online purchases. Subjective norms can be understood as the consumer's perception that most people who are important to him think he should or should not perform

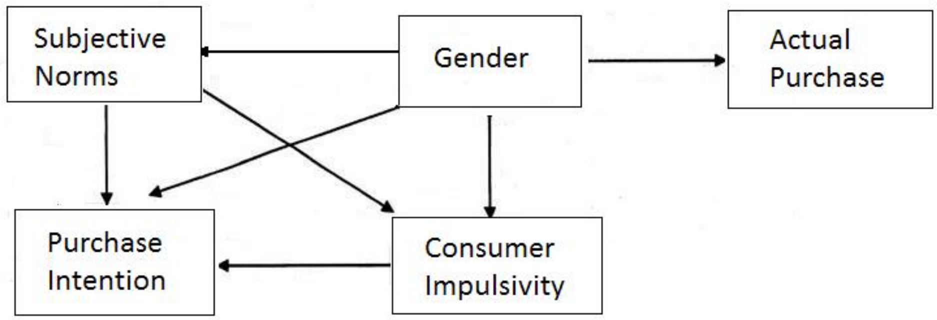

Figure 2–5: Factors influencing impulsive purchases. Adapted from Zhang et al. (2007) [4]

the behavior in question. Factors such as the pleasure and satisfaction influence consumers more easily and tend to be impulsive buyers. The impulse buying usually occurs in environments where there is more emotional activity. Zhang et al. [4], suggest that consumer's impulsivity is positively associated with purchase intention during online marketing exchanges. Gender differences exist among this sample with respect to purchase intention, consumer impulsivity, and frequency of purchase. Some elements of the web sites can function as stimulators for the realization of impulse buying.

On the other hand, customers that make their transaction electronically can be characterized in two ways. First, online buyers are also computer users. Using Technology Acceptance Model (TAM) one can see that the technology also provides a tool that can help vendors in their efforts to meet the task seller [4]. In this case, it is necessary to observe buyer's behavior interacting with the web site, both, having seen the web site as a shop as well as his/her perception as a technological system.

It is also necessary to study how consumer behavior influences buyer when choosing a particular product or brand. Harcar et al.[22], examines consumer behavior when he/she wants to choose a particular brand being offered in a shop. They developed a conceptual model that involves factors such as brand, price, perceived risk, familiarity with the product, psychosocial factors, demographic factors and product quality (Figure 2–6). It was found that there was an increase in sales of such stores as consumers understand that these brands offered by a particular store are very reliable. In addition, consumers usually associate price with quality. The behavior of the purchase was modeled on the basis that consumers already have to buy something.

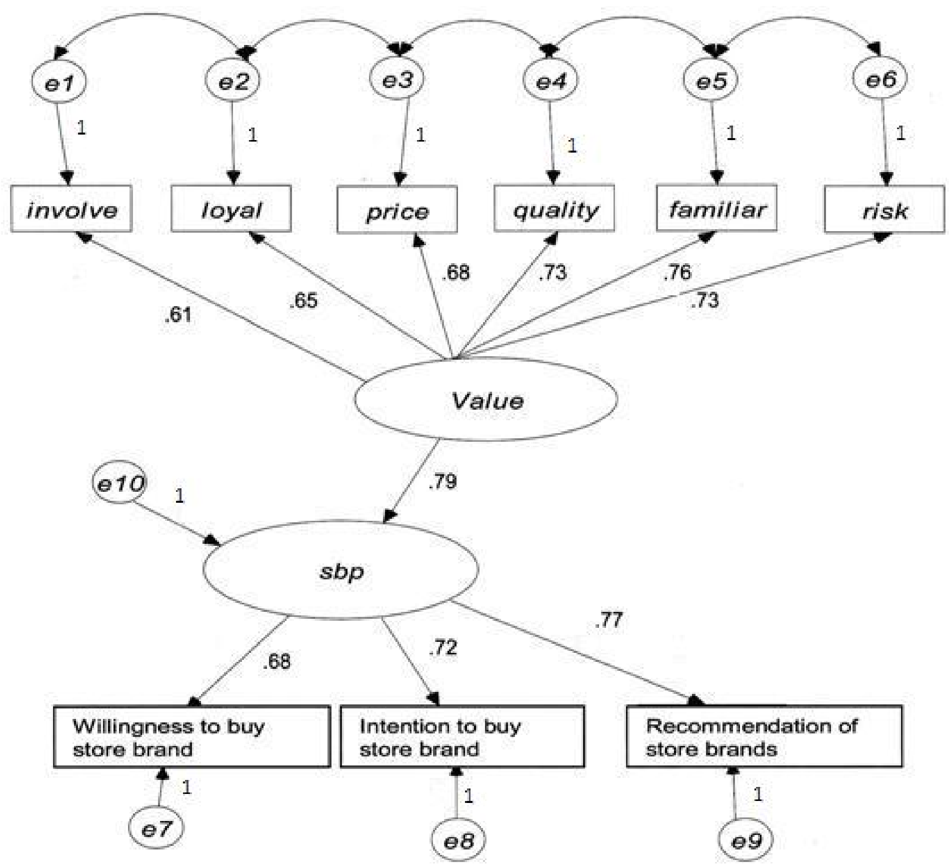

Figure 2–6: Path model for consumer behavior. Adapted from Harcar et al. (2006)[22]

Harcar et al. [22], defined perceived value as a multidimensional construct comprising involvement, brand loyalty, price perception, quality perception, familiarity and perceived risks.

On the other hand, the behavior of other consumers, e.g to hear what others are buying, has great influence in the decision to buy, despite the fact that one had already chosen the product. Another factor is that the price of a product can suddenly change, or there is another product that is more urgent to buy. However in online purchases, interaction with other buyers is smaller because it is almost like a private purchase. To improve this, many web sites provide information about the products sold by categories and prices, which is also an influential factor in deciding the product or brand of product to buy.

Observing purchase behavior from another perspective, i.e taking into account that a frequent visitor to the web site can become a buyer, Venkatech and Agarwal [19], suggest that web site use is a key indicator of the degree to which a site is "sticky". The usability factor is used to measure or predict the behavior of purchases on a website. As defined by International Standards Organization (ISO), usability is defined as "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use". This study also evaluated the factors that are the determinants in the usability of a web site. They considered demographic variables in consumer behavior such as age, gender and level of income (Figure 2–7).

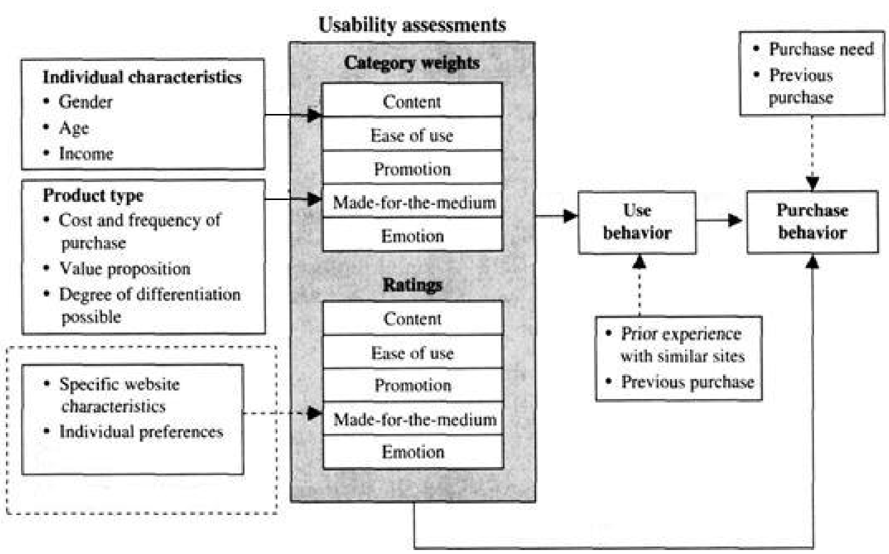

Figure 2–7: Usability perspective on purchase behavior. Adapted from Venkatech and Agarwal (2006) [19]

With regard to gender, if consumer behavior is more oriented to content rather than efficiency, there is a slight advantage for men. Age is a factor greatly in content and ease of use of the website. For consumers who have higher incomes, the content of the website is a very influential factor.

This literature review about the characteristics that influence consumer behavior in making purchases on the internet, beget an idea of the variables to be considered in the next stages of our research. The next step is to review the findings in the literature about the method we want to use in order to represent consumer behavior in the target population.

2.2 Agent Based Modeling

The environment of this research is an atmosphere characterized by uncertainty and risk. Those are often generated by the lack of knowledge about the processes involved in online transactions and sometimes by the risk of being deceptive with vendors who perform crimes on the Internet. In another sense, uncertainty and risk is generated simply because the own atmosphere of shopping online causes uncertainty due the veracity of products and lack of interaction with the seller. In this environment, consumers must rely on suppliers to make this a trustworthy environment for business.

The interaction between consumers occurs through existing social networks, as well as information transmitted by word of mouth. In this environment, consumers who will be represented as agents are connected with many other agents who somehow influence their behavior.

Due to the fact that in this type of environment, the agents' behavior does not act in a linear fashion, and that the decisions are influenced by a collective behavior, an agent based simulation seems to be a reasonable tool. This is also substantiated due the reach this methodology has to work in dynamic environments where interaction is an important factor in making decisions. This technique allows also reproducing patterns that can be observed in the real world.

2.2.1 What are agents?

At this point it is necessary to present the definition of the term "agent". In the literature there is no a universally accepted definition of the term agent. Weiss[23], presented this definition of an agent: "An agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives" (Figure 2–8).

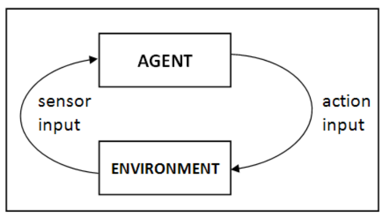

Figure 2–8: An agent in its environment

Agents are either separate computer programs or, more commonly, distinct parts of a program like in this case we are using to represent social actors such as consumers. They are programmed to react to the computational environment in which they are located, where this environment is a model of the real environment in which the social actors operate.

In that sense, according from a practical modeling standpoint [8], an agent has certain characteristics (Figure 2–9): An agent is identifiable, a discrete individual with a set of characteristics and rules governing its behaviors and decision-making capability, agents are self-contained. The discreteness requirement implies that an agent has a boundary and one can easily determine whether something is part of an agent, is not part of an agent, or is a shared characteristic.

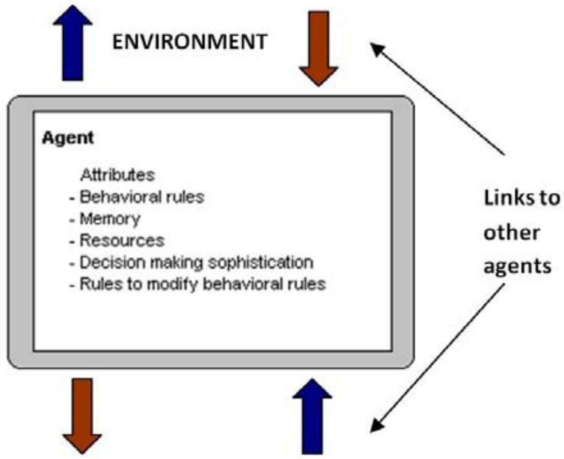

Figure 2–9: An agent in its general form

2.2.2 Agent-Based Models

Agent-Based models consist of agents that interact within an environment. A crucial feature of agent-based models is that the agents can interact, that is, they can pass information as messages to each other and act on the basis of what they learn from these messages [9]. The messages may represent spoken dialogue between people or other indirect message such as the observation of the behavior of another agent that could affect his/her own behavior.

An Agent-Based Model (ABM) is a computational model for simulating the actions and interactions of autonomous individuals in a network, with an objective to asses their effects on the system as a whole. It combines elements of game theory, complex systems, emergence, computational sociology, multi-agent systems, and evolutionary programming. In an attempt to re-create and predict the actions of complex phenomena, the model simulates the simultaneous operations of multiple agents. The process is one of emergence from the lower level of systems to a higher level. The individual agents are presumed to be acting in what they perceive as their own interests, such as reproduction, economic benefit, or social status, and their knowledge is limited. ABM agents may experience learning, adaptation, and reproduction [10].

In an Agent Based Model (ABM), agents represent entities in the real life. An agent has the capacity to store information about the beliefs, knowledge, goals and behavior of the entity which is representing, and it has also the ability to mimic a real-life entity [11]. An agent quite naturally represents the behavior of an individual in real life. This behavior tells us how an agent plays its roles within the system. The system defines rules programmed in advance to describe what the agent or agents are going to perform in certain circumstances.

Agents within the system have the ability to interact. This interaction also produces changes in the behavior of the agent and in the overall performance of the system [10]. However, there are changes that were not foreseen by the rules associated with each agent and result from their interaction and communication with each other. This collective behavior is known as emergent behavior, and this is one of the most important contributions of an ABM. Although this kind of emergent behavior is not explicit in the rules of the ABM, an ABM is capable of resolving and simulate such emergent situations [11]. A classic example of an emergent behavior we see in the natural way that have birds flying in "V" when they fly together. In this case, none of the rules of each individual agent (bird) is the resulting behavior. Emergent behavior only arises when these agents interact with each other.

Examples of emergent phenomena are also common in the social, political, and economic sciences. Human societies, biological ecosystems, the immune system, and distributed computation are examples of systems where such emergence is observed [24]. These phenomena can be difficult to predict or evaluate using traditional analysis. Bonabeau [10], classified four areas in which emergent phenomena may arise:

- Flows: Evacuation, traffic and customer flow management.
- Markets: stock market, software agents and strategic simulation.
- Organizations: operational risk and organizational design.

- Diffusion: diffusion of innovation and adoption dynamics.

Agent-based simulation has become popular as a modeling approach in the social sciences because, it enables one to build models where individual entities and their interactions are directly represented.

When simulating a system with ABM, an agent makes its decisions based on a set of rules that shape its behavior in a given situation. Agents can also run various behaviors according to the environment in which they are. This characteristic allows exploring dynamic modeling that is beyond the reach of mathematical methods [12]. An agent based model is a system of agents and their interactions with one another. The model can represent complex behaviors and provide valuable information about the dynamics of the real system that is representing.

Another very important aspect is that agents have the ability to evolve, and in some cases, adapting to another type of atmosphere, because the interaction between agents may require changes in their behavior. There are models that use techniques such as neural networks, evolutionary algorithms or other techniques that allow the agent to learn and adapt to a given environment [10]. Since, despite its easy implementation, ABM is still a difficult concept which might generate inappropriate uses of this technique, knowing when and how to use the ABM is very important to identify.

Macal and North [8], suggest situations for which agent-based modeling can offer distinct advantages to conventional simulation approaches, reveal new insights and answer long-standing questions. Hence, it could be beneficial to think modeling a system in terms of agents in the following situations.

- When there is a natural representation as agents.
- When there are decisions and behaviors that can be defined discretely.
- When it is important that agents adapt and change their behaviors.

- When it is important that agents learn and engage in dynamic strategic behaviors.
- When it is important that agents have a dynamic relationships with other agents, and agent relationships form and dissolve.
- When it is important that agents form organizations, and adaptation and learning are important at the organization level.
- When it is important that agents have a spatial component to their behaviors and interactions.
- When the past is no predictor of the future.
- When scaling-up to arbitrary levels is important.
- When process structural change needs to be a result of the model, rather than a model input.
- When the equations used to represent real social phenomena are too complicated to be analytically tractable, i.e when the system being modelled involve non-linear relationships as in the mayority of social word systems.

However, there are a lot of applications where ABM will not make much sense, being less efficient, harder to develop or not matching the nature of the problem. In those cases traditional tools like simulation of discrete events or system dynamics can efficiently solve those problems. Therefore, ABM is recommendable especially in the case the systems being modeled contains active objects such as people, business, animals, projects, products, etc, with timing, event ordering or other kind of individual behavior [12].

Among the advantages of the ABM we can mention the following:

- Capturing best behavior of a real system.
- It can manage behavior arising from the emerging learning and interaction with the other actors.

- It is flexible.
- An agent is able to make independent decisions, requiring an agent to be active rather then purely passive.

However, this versatility of ABM, comes at the price of “explanatory opacity” [13], meaning that the behavior of a simulation is not understandable by simple inspection; contrary, efforts towards explaining the results of the simulation must be expended, since there is no guaranty that what happens in it is going to be obvious (because emergent phenomena).

Since the highly abstract nature of ABM, the validation process of such systems is difficult. It is possible that the casual mechanism implicit in this complex system is flooded by the natural “turbulence” in the real word, and some entirely different sets of interactions of direct effects drive the formation of the feature of interest. Instead of the term “validation”, the term “empirical evaluation” is often used to emphasize the relaxed character of validating ABM, as opposed to the more demanding validation of engineering models of technical systems [13].

2.3 Multi agent systems.

A multi-agent system is a set of agents who have the aptitude to interact in a common environment. In this way, agents coexist in an environment with other agents and posses capacities of communication, negotiation, and coordination. Hence, agents develop the consequent learning capacity of behavior.

The idea of building a multi-agent system, not only serves to characterize a type of agent who provides services [25], but also can help the characterization of an agents who look for services and who must make decisions in uncertain and dynamic environments. Living in this environment, agents are seeking to satisfy a need maximizing some type of utility.

The paradigm of multi-agent systems is nowadays acceptable since they can solve complex problems than other techniques were known not to be satisfactory, especially in the case the system being modeled contains active objects (e.g people, animals, vehicles, business units, etc) [12]. Comparing with System dinamics or Discrete event models, there is no such plan in the Agent Based model where the global system behavior would be defined. Instead, the modeler defines behavior at individual level, and the global behavior emerges as a result of many individuals, each following its own behavior rules, living together in some environment and communicating with each other and with the environment [12].

A Multi-agent system has the capacity to play an important role in developing and analyzing theory models of interactivity in human societies [11]. Humans interact in various ways and at many levels: for instance, they observe and recreate behaviors, they request and provide information, they negotiate and discuss, they develop shared views of their environment, they detect and resolve conflicts, and they form and dissolve organizational structures such as teams, committees and economies. Many interactive processes among humans are still poorly understood, although they are an integrated part of our everyday life (agent based in social science).

2.4 Applications of Agent-Based modeling

Following, there is a summary of some investigations that use agent-based modeling for consumer behavior. These works use precisely the external and internal factors mentioned above, personalizing them according to the case study. They represent the factors believed to have more influence on the model conducted. Mehta and Bhattacharyya [24], developed an ABM of the electronic auction marketplace. They identified the auctioneer, the consumer and the retailer as the system's agents.

The agents interact in a manner specified by rules of interaction, in this case by offering to buy or sell quantities of commodities based on the current set of prices as dictated by the highest bidders (Figure 2–10). In their roles, only the auction, consumer, and retailer agents are modeled as "animate", in the sense that they are able to act autonomously and interact with other agents.

In this case there is no adaptable mechanism for any of the agent because the agent's behaviors were modeled from the objective of participation in a single auction. The customer agent does not have the ability to learn of bidding strategies when interact with the others, so it was disabled studying an emergent behavior of the customers.

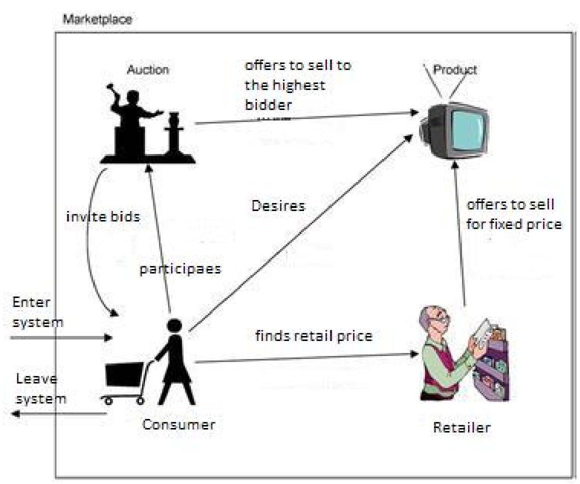

Figure 2–10: Schematic of the implemented Agent Based Simulation Model. Adapted from Mehta and Bhattacharyya (2006) [24]

Schenk et al.[26], presents an agent-based micro model for grocery shopping for representing the spatial choice to buy groceries, based on an individual population and store data gathered in Northern Sweden. The authors modeled the families as the simulation agents. The agent's variables include all their personal attributes, such as family size, income, habits, attitudes, lifestyles, coordinates of their residences, and a vector representing the attributes of their individual members. In this case, grocery stores are physically distributed along the territory, so the locations of stores have significance in the decision process. As a result they find that store earnings differ depending on whether they are located at residential streets or along highways.

Vag [27], presents a concept that integrates two approaches, conjoint analysis and multi-agent simulation. He used conjoint analysis to supply multi-agent models with behavioral data, while multi-agent simulation offers dynamics to the static results of conjoint analysis. This ABM takes the interactions and interdependencies between customers for understanding changing consumer behavior in their product preferences. The opinion-leader-status variable represents the persuasive power or ability of the agents to transmit a norm (i.e. product priority) in a communicative act. An opinion leader may convey its top-ranked product preference to other agents. Only those agents, whose source of-change variable is set to opinion leader, can accept the opinion leader's suggestion. The high-level structural elements of the model are the society, the individual and the market. The first block "Society" illustrates the product priority-changing communicative interactions among the consumers (e.g. interactions with reference groups and opinion leaders). The second element "Individual" highlights the product (or concept) preference changes as functions of post purchasing attributes (e.g. product satisfaction) and social communications (e.g. group-norm or opinion leader behavior) as well as the influence of current product preferences and consumer behavioral attributes (e.g. adoption) on purchasing motivations. The third block "Market" represents purchasing acts as functions of motivations and changes in the market-shares (Figure 2–11).

As we can see in the figure above, the motivations for continuous purchasing (or non-purchasing) may also depend on the previous product experiences. On the one hand, unsatisfied consumers do not purchase for the second time, and on the other hand, product satisfaction transforms individual product preferences and increases

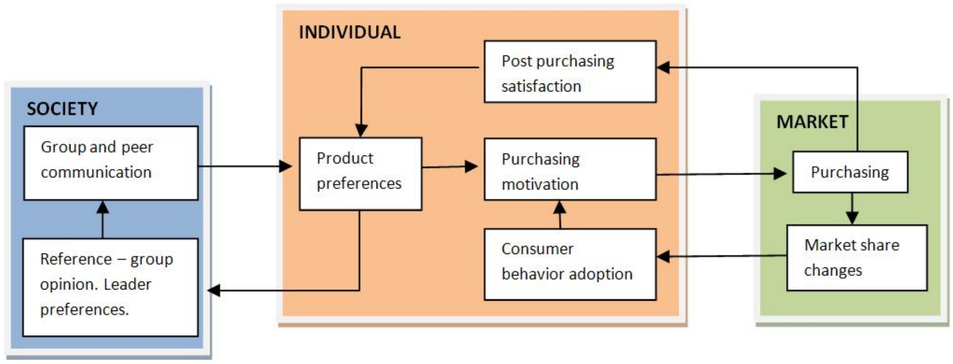

Figure 2–11: A dynamic conjoint model of product preference changes. Adapted from Vag (2007) [27]

purchasing motivations. Hence, the continuous change of product preferences within "Society" continuously affects group norms (group preferences) as well as the preferences of opinion leaders. However, this model ignores personality determination of shopping as we could see in the revised literature.

Zhang and Zhang [28], develop an ABM of consumer purchase decision-making combining consumers' psychological personality traits. This study uses multi-agent simulation (MAS) to exhibit the emergent decoy effect phenomenon, which is a market dynamic phenomenon originating from the individual behavior of heterogeneous consumers and their interactions in the real-world complex market. In this model, an agent has two types of interactions. One is the interaction between the agent him/herself and the brand managers. This type of interaction occurs in various forms of marketing activities. For example, interaction with respect to issues such as price, quality of the product, advertising, distribution channels, etc. The other type refers to the interactions among heterogeneous consumer agents (Figure 2–12 and Figure 2–13). One limitation of Zhang and Zhang model [28] is that ignores the self-learning ability of the agent that represents the consumers.

2.5 Summary

The ABM has been used in business problems involving mainly simulation of human systems, such as the spread of a new product in a population of consumers.

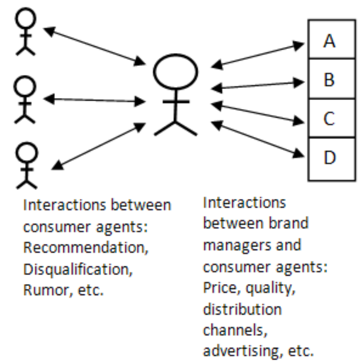

Figure 2–12: Two types of agent interaction.

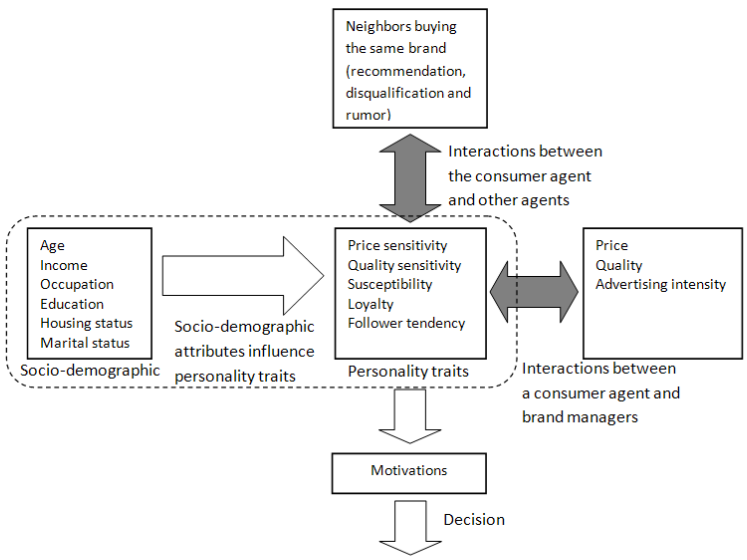

Figure 2–13: The purchase decision model. Adapted from Zhang and Zhang (2007) [28])

ABM can achieve a more realistic representation of consumer behavior. In this thesis, ABM helped us to represent the integration of consumer personality and socio-economics together, which is to treat the consumer decision process as the process of how the consumer intention has been formed.

There are also potential risks that are necessary to outline, such risks as those which consider the failures in the quality of service and risks which regard with the loss of information that is transmitted online. These risks are those that precisely make online customers have a different behavior from those who purchase in the traditional way. The model also captures the changing behavior of customers when they interact with one another.

In this literature review, we evaluated the agents and factors that will be used when carrying out the simulation model. We have seen that there are external factors that influence consumer behavior such as the characteristics of the Web site (reviews) and influences from other consumers (word of mouth, persuasive power). In addition, there are internal factors such as consumer's personality traits and socio-demographic characteristics such as age, gender, education, budget, etc. All of these factors act over the agent and influence his/her individual behavior on the environment that is going to be represented.

The idea of the construction of an autonomous agent, not only serves to characterize a type of agent that provides services [25], but also can help to characterize an agent who looks for services and who must take decisions in dynamic and uncertain environments, in which the agents are seeking to satisfy a need maximizing some type of usefulness.

Table 2–1, summarizes the factors identified that influence in consumer behavior and purchase intentions in traditional and electronic markets. In our case, these factors were represented in the ABM to characterize the influence on the behavior and decision making of online purchases.

Table 2–1: Summary of factors influencing consumer behavior and purchase intentions in traditional and electronic markets

Factor	Prior Research	Influence to	Definition
Subjective norms	[4]	Purchase intentions	Persons perception that most people who are important to him/her think he/she should or should not perform the behavior in question.
Impulsivity personality		Purchase intentions Subjective norms	
Gender		Purchase intentions Frequency of purchase Impulsivity	
Advertisement.	[29]	Brand confidence.	

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Table 2–1 ... continued from previous page

Factor	Prior Research	Influence to	Definition
Brand cognition.		Ad attitudes	
Distance. Individual preferences. **Store attributes.** **Individual preferences.**	[26]	Consumer behavior	Spatial distance to stores
Advertisement intensity. **Leader opinion.** **Satisfaction rate**	[27]	New product preferences. Spreading of worth-of-mouth. Post-purchase behavior.	
Gender **Age** **Level of income** **Product type** **Web content** **Web interface** **Time of web site usage**	[19]	Web site usability Web site usability Purchase intentions Purchase intentions Web site usability Web site usability Purchase intentions	
Affective **Need for cognition** **Neuroticism** **Agreeableness** **Openness to experience**	[20]	Willingness to by on line	Personal relevance of a shopping medium (hedonic and symbolic expectations) Interindividual differences in engaging in and enjoying cognitively demanding tasks.
Gender **Web site interface** **Product type** **Technology acceptance**	[7]	Online purchase behavior Satisfaction Online purchase intentions	
Product Knowledge	[18]	Likehood to choose a brand	Confidence in brand choice
Brand loyalty **Price perception** **Quality perception** **Familiarity** **Perceived Risk**	[22]	Store brand shopping behavior	

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Table 2–1 … continued from previous page

Factor	Prior Research	Influence to	Definition
Shopping goals	[18].	Consumer trust	Experiential and instrumental goals
Web interface design			
Web site characteristics: Easy of use, web content, security, privacy and interactivity)	[30].	Web site satisfactions	
Personal factors of web navigations (Reasons to visit a web site, need for cognitions, optimum stimulation level)	[5].	Web navigation behavior	
Situational factors of web navigation (Site involvement, exploratory behavior, attitudes toward a web site)			
Perceived risk	[31]	Willingness to purchase product.	Amount of perceived risk associated with purchase
Willingness to purchase		Post- purchase behavior	
Level of income	[32]	Consumer behavior	
Household size			
Innovativeness			Internet as an innovation to be adopted.
Interactivity		Consumer behavior	Characteristic of communication process that exerts impact through perceptions of communications.

The incorporation of those factors in the ABM, makes the simulation model reflects changes in customer behavior and purchase intention. Changes in behavior such as the way that a traditional consumer might turn into an online consumer and makes his/her purchases over the Internet. In addition, the model can reflect how other consumers who already use this medium could have an impact on traditional customers to make their purchases online. The model should also takes into account customer's personal characteristics and the environment that surrounds them (the market, the type of products, brands, group leaders, etc.).

Therefore, as revised and learned, we can expect that the ABM must answer the following question: How does the behavior of an individual consumer, especially their purchasing behavior change by the influence of external factors (website reviews, interaction with other actors) and internal factors (personal characteristics)?

CHAPTER 3
RESEARCH METHODOLOGY

The purpose of this chapter is to discuss the methodology used in order to achieve the objectives defined for this research and then to explain the development of the measurement instrument used to collect the data.

The diagram in Figure 3–1 shows an outline of the overall methodology and the sequence of procedures executed to assist in generating valid and reliable research results at each stage of this research. In addition, it is observed that each phase is linked to the next phase feeding the other not only with information but also validating the results obtained.

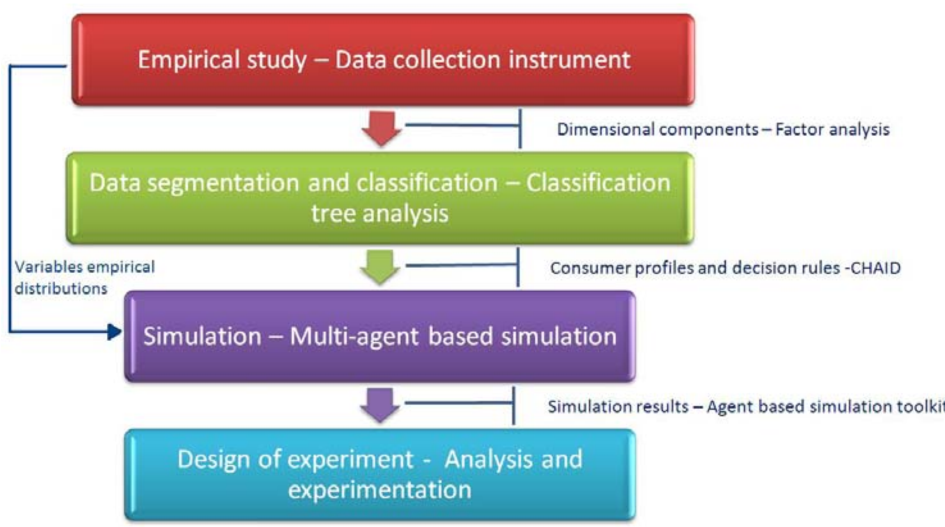


Figure 3–1: Research methodology

The first stage of this research was to perform an empirical investigation of extrinsic and intrinsic factors influencing online consumer behavior and purchasing intention. For this purpose, the first task was to identify the dimensional factors determined by a set of user characteristics that could moderate their consequent behavior.

An online survey was conducted to examine the empirical distribution of the external factors (i.e. web site rewiews and the interaction between the consumers) and the individual and situational moderating influences factors (i.e. social demographic and personality factors) influencing consumer behavior and purchasing intentions.

In the next phase we obtained the dimensional components derived from factor analysis and then used a classification tree analysis with CHAID (Chi-squared Automatic Interaction Detector) as a learning system to derive the decision rules from existing data in order to find significant patterns in the consumer's population.

The empirical distributions and the behavioral rules generated were used then to simulate the behavior of each consumer in the multi-agent based model. Using a computer model, this procedure is done in order to simulate a multitude of individual entities and then explore the consequences the rules specified at the individual level have on the entire population of agents.

The simulation results were then analysed using a factorial design to explore the effects of different initial conditions on the dependant variable.

3.1 Conceptual model

A conceptual model was developed in order to identify personality traits useful for predicting purchasing consumer behavior online. In this model (Figure 3–2), a consumer represents an individual that intends to purchase a product or a service online. Therefore, electronic commerce represents in this case, the environment where this consumer lives and interacts. Here, the consumer will show their behavior influenced by intrinsic and extrinsic factors coming from socio-demographics characteristics, personality and the online medium per se.

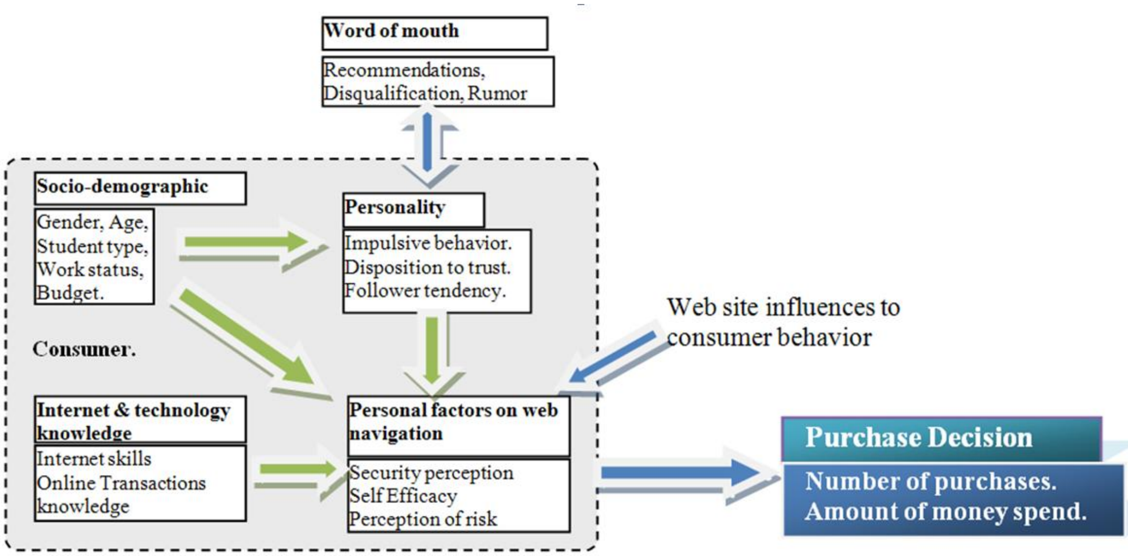


Figure 3–2: Research Conceptual Model

Consumer intrinsic factors clustered in four groups: Socio-demographic factors, personality factors, personal factors on web navigation and internet and technology knowledge. Socio-demographic factors include gender, age, student type, work status and budget. These factors appear to influence consumer personality characteristics [14], [33], [34], [6] and [35]. Personality determinants considered in this research are impulsive behavior, disposition to trust and follower tendency [34], [36], [37] and [38] (these represent the level in which a consumer is prone to follow recommendations or disqualification from others by word of mouth). For example, the opinion of a leader represents the persuasive power or ability to transmit a norm in a communicative act. An opinion leader may convey its preferences to other consumers.

Both socio-demographic factors and personality factors influence personal factors of web navigations, which are the perception a consumer has when visiting a web site [6], [35] and [37]. Internal factors described earlier generate the purchase motivation in an online environment and then cause the purchase decision. Personal factors of web navigations are influenced by external factors identified in this model as the characteristics of a web site, such as the richness of a web site interface and the level of security that offered by this web site for doing online transactions, [6], [35] and [37].

Finally, the last group represents the level of knowledge respondents have about internet, security in online transactions and online shopping procedures. The skill level a user has in internet was categorized as “novice”, “with some experience”, “advanced” and “expert” [39].

3.2 Development of the data collection instrument

For developing the questionnaire, it was necessary to prepare a sample of questions. These questions are expected to measure the dimensions we are considering as factors that influence consumer behavior. The items for the questionnaire were mostly adapted from prior research and grouped to form the constructs in this thesis.

Nine sections were developed for this questionnaire. Each of which were designed to measure a construct that represents the latent variables proposed by previous investigations.

Section 1: Socio economic characteristics

The first section of the questionnaire captures subject’s socio-economic characteristics such as age, gender, education, work status as well as the number of online purchases they have made and the amount of money destined for that activity (Table 3–1). The average number of online purchases made, gives an indication of the subjects’ experience as online shoppers [35]. Previous studies have examined the socioeconomic factors to assess whether there are differences in consumer segments [14], [33], [34], [6], [35] and [40] .

Table 3–1: Factors considered in socio economic section:

Author (s)	**Variables**	**Year**
Price [34]	Age, gender, and ethnicity. Number of previous internet purchases. Amount of money spent in online shopping last year.	2004
Tielman [40]	Age, gender and culture Prior experience, referent influence, value of spending, perceived reputation of web sites.	2003
Sullivan [6]	Age, Gender, income, education level and occupation	2003
Veena [35]	Use age, gender, number of purchases made via internet.	2005
Park [33]	Ethnicity, marital status, and also money spend on online shopping	2003
Lorenzo [14]	Gender, age, income and education. Amount of money a university student has for his/her own expenses.	2005

Those studies were used to describe, explain, compare and evaluate the relationships among the effects of consumer demographic and consumer socialization factors on trust in, satisfaction with, and loyalty to web merchants [40]. Chapter Four investigated whether a consumer's age, gender and cultural background had an influence on the frecuency of online purchases.

Sullivan [6], stated that socio economical factors are determinants in online shopping preferences (age, gender, income, education level and occupation). Also Sullivan's respondents answer according to the type of product they have bought online. To measure how much money will be used to purchase online, Lorenzo [14], makes a question about how much money a university student has for his/her own expenses.

Range of ages for the questionnaire can be categorized according to age cohorts that were deemed important and influence in the behavior of an specific group of people. Kim [41] included groups of ages rather than an open question about age.

These groups of age was distributed as follow: Less than 18, 18 - 30, 31 - 40, 41-50, 51 - 65, 65 or more.

Demographically speaking, cohorts represent groups of people who were born during a certain time period and who had in common factors such as the same life experiences, tastes and preferences [42]. Table (3–2) presents a list of chart generation developed by Howe and Strauss [43], representing the characteristics of every cohort and the time interval that separate each generation.

Table 3–2: Howe and Strauss [22] Chart Generation

Era	**Generation**	**Sub-Generation**	**Time table**	**Notable ocurrences**
Jazz Age (Great Depression and World War II)	Greatest Generation	G.I. Generation	1911 - 1924	*Experienced WWII in adulthood*
		Silent Generation	1925 - 1945	*Experienced WWII in childhood*
	Baby Boomers		1946 - 1956	*Civil Rights Movement*
Consciousness Revolution (Vietnam War / Counterculture / Cold War)	Generation Jones	Beat Generation / Hippie	1957 - 1964	*"First modern counterculture"*
			1965 - 1974	*Rise of the Arcade/*Atomic Age
	Generation X	Baby Busters	1975 - 1981	*Experienced Vietnam War/Cold War*
		MTV Generation / Boomerang Generation	1982 - 1987	*Rise of Mass Media/end of the Cold War*
Culture Wars (War on Terror / Iraq War / Neoconservatism)	The Millennial Generation	Echo boom	1988 - 1992	*Dawn of the 21st century/*War on Terror
		iGeneration	1993 - 1999	*Rise of the* Information Age/*Internet*/War on Terror/Iraq War
	Global Generation		2000 —	Digital Globalization

For the purpose of this research we are taking into account six age cohorts ranging from "Silent generation" to the "Echo boom generation". It was considered inappropriate to separate the early age groups because it is assumed that people over 62 years (by the date on which this investigation took place) have a similar behavior when making purchases over the Internet. In that sense the ranges of the variable age (in years old), were carried out as follows:

- 16 - 20 (Echo boom generation)
- 21 - 26 (MTV Generation/ boomerang Generation)
- 27 - 33 (Baby busters)
- 34 - 43 (Generation Jones)
- 44 - 51 (Beat Generation / Hippie)
- 52 - 62 (Baby Boomers)

Section 2: Disposition to trust

Disposition to trust can be defined as customer personality trait that leads to generalized expectation about the trustworthiness [37]. Disposition to trust is also defined as a general willingness based on the formation of human relationship to depend on others [16]. Hoon [37] posited that more consumers are disposed to trust the other party, the less amount of risk they are likely to perceive. He has demonstrated that disposition to trust is negatively associated with perceived risk and disposition to trust is positively associated with consumer's trust. The scale to measure disposition to trust was assessed by using items from prior study in electronic commerce context [37]. This consists on five items in a 7- point likert scale; from strongly disagree to strongly agree (Table 3–3). The reliability coefficient calculated by Hoon [37] for this construct has a value of alpha = 0.862. Variable names were assigned to each of the five questions in order to uniquely identify them.

Table 3–3: Disposition to trust

Variable name	Question Item
DispTrust1	I generally trust other people.
DispTrust2	I tend to rely on other people.
DispTrust3	I generally have faith in humanity.
DispTrust4	I feel that people are generally reliable.
DispTrust5	I generally trust other people unless they give me reasons not to.

Section 3: Questions about impulsive buying

This section contains questions designed to measure customer's impulsive buying behavior. The scale to measure impulsive buying was assessed by using items from Sun et al. [44]. Sun et al. [44], in turn, used a combination of buying impulsiveness scale developed by Rook and Fisher [45] and impulse buying tendency scale by Weiun et al. [46]).

The scale consist on 14 items, measured on a 7- point Likert scale from strongly disagree to strongly agree.

Sun et al. [44], calculated the Cronbach's alpha for the 14-items resulting in a value of alpha = 0.90, which is a very acceptable value. Impulsive questions were thus averaged to form an overall score that measures impulsive buying.

Again, variable names were assigned to each of the 14 questions (Table 3–4).

In an online context, Veena [35] developed a model that represent impulsive buying behavior, and confirm that this behavior is a result of emotional reactions. Her study has demonstrated that to increase the likelihood that the consumer will engage in an impulse purchase, hedonic reactions to the interface should be maximized, while keeping negative cognitive reactions to a minimum. Negative cognitive reactions should be minimized by ensuring that the website is secure and easy to navigate and the emotional reactions to the interface should be maximized by using an innovative and creative interface design.

Table 3–4: Impulsive buying

Variable Name	Question item
ImpBhvior1	I often buy things spontaneously.
ImpBhvior2	"Just do it" describes the way I buy things.
ImpBhvior3	I often buy things without thinking.
ImpBhvior4	"I see it, I buy it" describes me.
ImpBhvior5	"Buy now, think about it later" describes me.
ImpBhvior6	Sometimes I feel like buying things on the spur-of-the-moment.
ImpBhvior7	I buy things according to how I feel at the moment.
ImpBhvior8	I carefully plan most of my purchases (reverse-coded).
ImpBhvior9	Sometimes I am a bit reckless about what I buy.
ImpBhvior10	When I go shopping, I buy things I had not intended to purchase.
ImpBhvior11	I am a person who makes unplanned purchases.
ImpBhvior12	When I see something that really interests me, I buy it without considering the consequences.
ImpBhvior13	It is fun to buy spontaneously.
ImpBhvior14	I avoid buying things that are not on my shopping list. (reverse-coded)

Section 4: Technology knowledge

This section is designed to capture the level of knowledge respondents have about internet, security in online transactions and online shopping procedures. Seven questions were developed to capture these consumers' characteristics (Table 3–5).

According to Li [47], the scale to measure the experience with the use of internet (Skill variable in the questionnaire) is based in the answers respondent's made in four specific assertions:

1. Read and write e-mails, browsing news.
2. Find and compare information.
3. Share information posting in a web site (text, videos, photos, etc)
4. Create and publish a web page.

Then to categorize the skill level a user has in internet, Li [47], proposed the following statements:

- A respondent is "Novice" If only assertion 1 is selected.
- If items 1 and 2 were selected, the respondent is considered with "some experience".

- Selecting up to item 3, the respondent is considered “advanced”.
- “Expert” if selected all items.

Table 3–5: Technology knowledge

Variable name	Question/item
Hours	How many hours per week do you spend on computer? (including spending on the web)
Skills	Check the item if you have the ability to:
	Read and write e-mails, browsing news.
	Search for information over the internet.
	Share information posting in a web site (text, videos, photos, etc)
	Publish a web page
Secure	Do you know how secure is your information (payment/ transaction information) when you realize purchases online?
PersInfo	Do you know what personal information does a web site gather?
Shares	Do you know if a web page shares the information it receives?
Services	Do you know about services that enable businesses and people to make secure transactions over internet? (e.g Vesirign, TRUSTe, secure sockets layer)
Phising	Are you aware about identity fraud on internet? (e.g phishing).

Section 5: Security perceptions

Security perceptions are conceptualized as the subject’s subjective beliefs that “their private information will not be viewed, stored, and manipulated during transit and storage by inappropriate parties in a manner consistent with their confident expectations” [35].

The different items asked the subjects whether they believed that the information they provided at the website will be transmitted securely and stored properly.

The measure used was adapted from Vehna [35], and consist on a 6-item scale, measured on a 7-point Likert scale, from strongly disagree to strongly agree.

The variables representing the questions in this construct were defined as in Table 3–6:

Table 3–6: Security perception

Variable name	Question/item
Trus1	I am confident that the information I provide during any transactions will not reach inappropriate parties during storage in web retailer's databases.
Trust2	I believe inappropriate parties cannot deliberately observe the information I provide during my transaction with a web retailer during transmission of data.
Trust3	In my opinion, inappropriate parties will not collect and store the information I provide during my transaction with this web retailer.
Trust4	In general, I do not trust the purchasing process in the web site as much as I trust traditional purchasing processes. (reverse-coded)
Trust5	Overall. I have confidence in the security of my transaction with a web retailer.
Trust6	The web site I use to make shopping is trustworthy.

The reliability coefficient for the construct "security perceptions" produced a Cronbach's alpha coefficient of 0.97 [35].

Section 6: Perceptions of risk

This section contains questions designed to capture the perception of risk regarding the web site(s) that a customer has when making online purchases.

Perception of risk, in the context of online transactions, can be defined as a consumer's belief about the potential uncertain negative outcomes from the online transaction [37].

The scale to measure perceived risk in the context of online transactions was developed by Hoon Young [37], and consists on 6-item scale measured on a 7-point Likert scale that range from absolutely no risk to significant risk, or, very negative situation to very positive situation, or, very unlikely to very likely, or, strongly disagree to strongly agree (Table 3–7).

The Cronbach's alpha reliability coefficient was calculated obtaining an alpha value of 0.854 [37]. Five items on a 7-point Likert scale were adapted to measure respondent's perceptions of risk in relation to the web site visited when making an online purchase.

Table 3–7: Perception of risk

Variable name	Question/item
PercepRisk1	How much risk would you tolerate when deciding to make a purchase from the web sites?.
PercepRisk2	How would you rate your overall perception of risk from a web site?.
PercepRisk3	How would you characterize your experience with the web site as it relates to making a purchase decision? (reverse-coded)
PercepRisk4	Purchasing from a web site would involve more product risk (i.e not working, defective product) when compared with more traditional ways of shopping
PercepRisk5	Purchasing from a web site would involve more financial risk (i.e fraud, hard to return) compared with more traditional ways of shopping.

Section 7. Online transaction self-efficacy

In the context of online transactions, individuals with higher general self-efficacy are expected to perceive less risk in e-commerce. More specifically, if people are confident that they are usually able to purchase exactly the item that they want from web vendors, they are more likely to trust a web vendor and make purchases in the future [37].

The Cronbach's alpha reliability coefficient was calculated by Hoon Young and obtained a value of alpha = 0.854.

A six-item scale was developed by Hoon [37], for measure on line transaction self-efficacy in a Business-to-Consumer e-commerce environment. The scale consists on a 7-point-Likert scale, ranging from strongly disagree to strongly agree (Table 3–8).

Table 3–8: Self-Efficacy

Variable name	Question/item
SelfEfficacy1	I am confident that I can obtain relevant information through online source (e.g., online discussion groups, reputation sites, etc) on the Web vendors whom I am planning to make online purchases.
SelfEfficacy2	I am confident that I am usually able to purchase exactly the item that I want from Web vendors.
SelfEfficacy3	I am confident that, in case my order does not come through in a satisfactory manner, I am able to take care of the problems of my own.
SelfEfficacy4	I am confident that I am able to find a trustworthy web vendor based on ratings (e.g. number of the start or the smiley faces) provided by other consumers.
SelfEfficacy5	I am confident that in case of merchandise I have purchased online turns out to be defective, I am able to return it without any problem.
SelfEfficacy6	I am confident that, if the web vendor I made an online purchase from would not take back a defective product, I am able to solve the problem through the assistant of a third party (e.g. friends, better business bureaus, or relevant governmental agencies

Section 8. Word of mouth

Word of mouth phenomena is a reference to the passing of information from person to person.In an online environment the internet dramatically facilitates consumer interconnections. Email referrals, online forums of users and newsgroups, as well as customer reviews encouraged by merchant websites allow consumers to share information far more easily than ever before [36]. This interconnectivity is a global phenomenon that facilitates the dissemination of both positive and negative word-of-mouth.

To meassure this phenoma we developed five questions measured on a 7-point Likert scale, ranging from strongly disagree to strongly agree.

Those questions were made in order to capture both word of mouth phenomena (Table 3–9). One comming from the reviews presented on the web site and the other from succesfull experiences in online purchases made by other people.

Table 3–9: Word of mouth

Variable name	Question/item
Wom1	I often influence other people in using the Internet for buying products or services.
Wom2	Other people see me as a good source of information to make purchases on the Internet.
Wom3	If I have the intention to buy a product on a website, my decision to purchase is based on the positive shopping experience of others (friends/relatives/user forums).
Wom4	When I buy a product online, the reviews presented on the website make me confident in purchasing the product.
Wom5	I buy via Internet since I see that others make secure purchases by this medium.

Table 3–10 shows a summary of the five constructs (without socio-demographic characteristics and technology knowledge) with their reliability coefficient calculated by previous studies.

Table 3–10: Constructs generated and Cronbach's alpha.

Construct	Number of items	Cronbach's alpha	Scale	Author
Disposition to trust	5	0.862	7- point Likert scale	[37].
Impulsive behavior	14	0.90	7- point Likert scale	[44],
Security perceptions	6	0.97	7 – point Likert scale	[35],
Perceptions of risk	6	0.854	7- point Likert scale	[37]
On line transaction Self-efficacy	6	0.881	7- point Likert scale	[37]

3.3 Empirical analysis

The sample for our survey was composed mostly of a young adult population (i.e undergraduate and graduate college students). This population seems to be appropriate for this survey because they generally spend considerable time on the internet and represent the next generation of consumers. Moreover, they have been using the latest information technology devices throughout their daily activities.

For doing the survey, an online questionnaire was designed and administered. The questions captured personality aspects and social-demographic characteristics of each respondant.

For the population segment in this research, the statistical analysis of this survey provided us with the empirical distributions of the factors taking into account for the simulation. These distributions served as the input parameters in the creation of agents for the simulation.

3.3.1 Pre-test of the instrument (pilot experiment)

To ensure the validity of the study, it has been suggested that pilot studies should be considered to address any issues associated with the task or the constructs used [35].

The questionnaire was pre-tested using a convenience sample of 40 participants. Most of the participants were recruited by the researcher in the department of Industrial Engineering at the University of Puerto Rico in Mayaguez. The majority of the participants (33 respondents, 82.5%) in the pre-test sample were students between the ages of 16 and 26. The others were friends and people that the researcher considered appropriate for the pilot experiment. The questionnaire instrument was given in the actual experimental setting. The researcher asked each participant if the questions were clear and also if the web page operates properly. This analysis indicated that there were only minor wording improvements needed. Formatting of the questions seems to work well for all the respondents.

In order to detect multicolinearity problems (i.e. items measuring the same thing) the sample correlation matrix was first analyzed. Therefore, questions with an inter-item correlation value greater than 0.80 were eliminated. Finally, a group of questions were added since at first instant, the word of mouth phenomena was not considered in the pilot questionnaire. For details about the pilot experiment see APPENDIX A.

3.3.2 Factor analysis

The data was collected through the use of an online questionnaire made accesible via a web site from the departament of Industrial Engineering at the University of Puerto Rico in Mayagüez. The survey were conducted in classrooms having internet connection. Most of the participants were students from the department of Industrial Engineering, while others belonged to the department of Mathematics, Electrical and Computer Engineering and others. During survey administration, each participant was instructed to first read the instructions and agreed with the consent form, then he/she completed the whole questionnaire. The final version of the questionnaire is shown in Appendix B.

The final sample consisted on 751 respondents and was used to conduct the analysis using SPSS 16 for Microsoft Windows. Table 3–11, summarizes the demographics of the sample. This sample was composed mostly of a young population (88.7% between the ages of 16 and 26). Most of the subjects in the sample are university students (92.6%) all of them living in Puerto Rico.

Factor analysis allows the researcher to identify and separate dimensions of the structure. Also it determines the extent of which each variable is explained by each dimension. Once each dimension is determined, factor analysis allows synthesizing and reducing the amount of data used. By synthesizing the data, factor analysis extracts dimensions that describe the characteristics of the original data. The dimensions generated, can replace the original variables if factor analysis is well-executed [48].

In factor analysis, all variables relate to one another to form factors that maximize the explanation of all variables identifying the structures existing between them.

Since the study was exploratory in nature, a principal components analysis was carried out. Varimax rotation was selected to maximize the loading of each variable on one of the extracted factors while minimizing the loading on all other factors. The objective of the rotation of factors is to redistribute the variance to obtain a pattern of factors with a greater meaning [38]. Also, the interest of the Varimax rotation is that it allows to have and easier interpretation of the factors [35]. Varimax rotation indicates a clear positive or negative association between the variable and the factor (or lack of association if the value is close to zero).

Table 3–11: Descriptive statistics. Respondent's socio-economic characteristics

Demographic Variable	**Frecuen cy**	**Percentage**	**Demographic Variable**	**Frecuen cy**	**Percentage**
Gender	–	–	**Times (purchases made in the last six months)**		
Male	364	48.5	None	292	38.9
Female	387	51.5	< 5	363	48.3
Age			6-10	51	6.8
16-20	343	45.7	11- 20	28	3.7
21-26	323	43	20 - 40	5	0.7
27-33	47	6.3	40 >	7	0.9
34-43	25	3.3	—	—	—
44 +	13	1.7	—	—	—
Type of student			**Spend (money spend in the last six months)**		
Undergraduate	627	83.5	Nothing	292	38.9
Graduate	68	9.1	$1 - $ 200	245	32.6
Non-students	56	7.5	$201 - $400	85	11.3
Work status			$401 - $600	51	6.8
Not working	483	64.3	$601 - $800	32	4.3
Partial	176	23.4	$801- $1000	15	2
Full time	92	12.3	> $1000	26	3.5
Budget for own expenses (monthly)					
< $100	127	16.9			
$100- $200	208	27.7			
$201 - $300	152	20.2			
$301- $ 500	150	20			
> $500	109	14.5			

With the Principal Component Analysis, it is possible to determine the number of factors to choose in factor analysis. There are two possible approaches to determine the number of factors:

1. Kaiser-Guttman rule suggests that only factors with eigenvalues over 1.00 are to be extracted [49].
2. Thompson's [50] approach suggests that the number of factors extracted is related to the cumulative contribution of factors, taking the number of factors which cumulative contribution is greater than 70%.

The number of factors considered in this research was determined following the two approaches outlined above. Based on the first rule, the factor analysis obtained in this study, provided a nine-factor solution. While taking into account the second rule, a seven-factor solution was obtained.

Following the rule of Kaiser-Guttman [49], the solution was obtained by rotating all factors with eigenvalues greater than one. The results from this study seemed promising since it was possible to summarize 62.3% of the variance with nine factors. We also found that it was rather easy to name each of the factors. These results are presented in Table 3–12 showing items having loadings greater than 0.40.

To test the appropriateness of factor analysis, the Kaiser-Maier-Olkin (KMO) measure of sample adequacy and Barlett's test of sphericity were conducted. The KMO in this case was 0.858 and the Barlett's test of sphericity reveals a significant level of 0.000 (chi-square = 12330.61 and df = 703), hence these values confirm the sufficiency of the sample for factor analysis.

The constructs generated from the factor analysis were then renamed to better identify the dimensions to be used for the next stages of this thesis.

- Construct 1 - Impulsive behavior (ImpBvior1, ImpBvior2, ImpBvior3, ImpBvior4, ImpBvior5, ImpBvior6, ImpBvior7).

- Construct 2 - Self Efficacy (SelfEfficacy1, SelfEfficacy2, SelfEfficacy3, SelfEfficacy4, SelfEfficacy5).
- Construct 3 - Disposition to trust (DispTrus1, DispTrus2, DispTrust3, DispTrus4, DispTrus5).
- Construct 4 - Word of mouth (Wom1, Wom2. Wom3, Wom4, Wom5).
- Construct 5 - Knowledge in online transactions (PersInfo, Secure, Shares, Services, Phishing).
- Construct 6 - Perception of risk (PercepRisk3, PercepRisk4, Trust3).
- Construct 7 - Security perception (Trust1, Trust2).
- Construct 8 - Risk tolerance (PercepRisk1, PercepRisk2).
- Construct 9 - Internet Skills (Hours, Skill, ImpBvior8).

3.3.3 Reliability analysis

Reliability analysis was performed based on Cronbach's alpha (Table 3–13), an important and widely used measure for assessing the internal consistency of a set of items [51].

The coefficient alpha was described in 1951 by Lee J. Cronbach. It is an index used to measure the internal consistency reliability of a scale, i.e. to assess the extent to which items of an instrument are correlated [52]. In other words, Cronbach alpha is the average number of correlations among the items that are part of an instrument [51]. Also this ratio can be thought of as the extent to which some construct, a concept or measured factor is present in each item [53].

Table 3–12: Rotated component matrix - 9 components

	Component								
	1	2	3	4	5	6	7	8	9
ImpBvior3	.880								
ImpBvior5	.838								
ImpBvior4	.833								
ImpBvior2	.824								
ImpBvior1	.780								
ImpBvior6	.730								
ImpBvior7	.724								
SelfEfficacy5		.809							
SelfEfficacy3		.776							
SelfEfficacy6		.729							
SelfEfficacy4		.711							
SelfEfficacy2		.644							
SelfEfficacy1		.472							
DispTrust1			.854						
DispTrust5			.784						
DispTrust2			.782						
DispTrust4			.773						
DispTrust3			.696						
WOM5				.760					
WOM3				.725					
WOM4				.711					
WOM1				.677					
WOM2				.647					
PersInfo					.781				
Secure					.748				
Shares					.735				
Services					.722				
Phishing					.421				
PercepRisk4						.838			
PercepRisk3						.833			
Trust3						.651			
Trust2							.770		
Trust1							.735		
PercepRisk1								.839	
PercepRisk2								.645	
Hours									.634
Skill									.628
ImpBvior8									.470

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

The minimum acceptable value for the Cronbach's alpha coefficient is 0.60. Below this value the internal consistency of the utilized scale is low. On the other side, the maximum value expected is 0.90, above this value it is considered that there is redundancy and duplication, i.e. that several items are measuring exactly the same element of a construct, so redundant items should be eliminated [53]. Usually, values of alpha between 0.70 and 0.90 are preferred. However, when there is not a better instrument, it can be accepted lower values of alpha [51].

Table 3–13: Reliability Coefficients

Construct	**Cronbach's alpha**
Impulsive Behavior	0.910
SelfEfficacy	0.864
Disposition to trust	0.851
Word of Mouth	0.824
Knowledge in online transactions	0.787
Risk Perception	0.765
Security Perceptions	0.726
Internet Skills	0.304
Risk tolerance	0.459

Cronbach's alpha except for two constructs (Internet skills and Risk tolerance) ranges from 0.726 to 0.910. therefore seven components fall in the acceptable region. Those variables whose Cronbach's alpha resulted in a low level, were treated as individual variables for determining the predictors of purchase intention. On the other hand, those variables whose inclusion in a construct generate a lower level in the Cronbach's alpha were eliminated from its contructor and treated then as individual variables (i.e Trust3 in construct "Risk Perception" and Phishing in construct "Knowledge in online transactions".)

This empirical study has shown that the resulting seven factors are consistent with previous studies [35], [36], [37], [40] and [54] and also adjusted very well to the variables defined in the conceptual model. The level of reliability obtained in each of the constructs also demonstrates the strength of the measuring instrument developed.

Therefore, the seven dimensions components resulting from factor analysis and in along with socio-demographic variables became the predictors for consumer behavior variables in the population represented by this sample. In this case, the target variables were defined as the number of times and the amount of money spent by consumers in the past six months as defined in the conceptual model.

CHAPTER 4
CLASSIFICATION TREE ANALYSIS

This chapter describes a prediction model for exploring consumer behavior in e-commerce. We used classification tree analysis with CHAID (CHi-squared Automatic Interaction Detector) as a learning system to derive the decision rules from existing data in order to find significant patterns in the consumer's population.

The aim of this chapter was to determine decision rules to predict future behavior in online purchases. Also, these decision rules will allow us to classify consumers in different groups each presenting a particular behavior that follows a set of rules with certain likelihood. For this purpose, independent variables were grouped in seven dimensional components derived from the factor analysis done in Chapter three. In addition to those variables we include socio-demographic variables to became the predictors for consumer behavior. The contribution of this chapter is to specify the rules of behavior for a group of customers, as well as the rules of their interaction. That information will be used then to program the decision rules that govern the behavior of the agents in the multi-agent based simualtion.

Classification tree analysis is one of the basic modern data mining methods [55], which synthetically compares independent variables and automatically choose those variables that mostly affect the objective. Hence, this technique is used to find the optimal classifying mode. In this chapter we have demonstrated the application of classification tree analysis to obtain different consumer profiles based on factors that mostly influence their behavior in online purchases.

When using classification tree analysis, there is a dependent variable whose distribution is wanted to be explained and, on the other side, there is a set of independent variables called predictors whose objective is to form very different groups (profiles) in the dependent target variable. Based on the data collected from the questionnaire and using a classification tree technique we want to construct decision rules for each resulting group in order to predict future behavior in online purchases.

A Classification tree is a type of Decision tree that illustrates the decision rules which are both descriptive and predictive so the tree has the property to describe the available data and then predict unseen data [39]. The objective in using classification tree analysis in this research is to classified likely versus unlikely consumer who buy online based on respondents characteristics that represents their behavior.

4.1 The CHAID procedure

The logical steps in doing a classification tree analysis begin with the definition of the dependent variable and the selection of a set of possible relevant predictors [56]. Bearing in mind these considerations, the seven dimensions previously found were taken into account and form the first group of predictor variables *(Impulsive Behavior, Self Efficacy, Disposition to trust, Word of mouth, Knowledge in online transactions, Risk perception and Security perception)*, while along with socio-demographic variables became the group of independent variables called predictors (Table 4–1).

In this reseach we defined the amount of money spent and the number of times respondents made online purchases as the dependent variables (Table 4–2). Then we applied the classification tree analysis to deeply analyze the influences of independent variables on each dependent variable to finally observe the possible association rules existing among independent and dependent variable.

Table 4–1: Independent variables (Predictors)

Predictor Name	Description	Type	Scale
	Socio-Economic variables		
Gender	Consumer gender	Nominal	F = Female, M = Male
Age	Age of the respondents grouped in six cohorts.	Nominal	16 - 20 21 - 26 27 - 33 34 - 43 44 - 52 more than 52
Work_Stus	Work status	Ordinal	Not actually working Partial worker Full time worker
Std_Level	Education level	Ordinal	High School Bachellor degree Master degree Doctoral degree
Income_L	Family income level	Ordinal	Less than \$25,000 \$50,000 - \$75,000 \$75,000 - \$100,000 more than \$100,000
Budget	Personal budget for expenses	Ordinal	Less than \$100 \$100 - \$200 \$201 - \$300 \$301 - \$500 more than \$500
	Dimensions from factor analysis		
ImpBvior	Impulsive Behavior	Ordinal	7-point Likert scale (Table 3–4)
SelfESum	Self Efficacy	Ordinal	7-point Likert scale (Table 3–8)
DispTrust	Disposition to trust	Ordinal	7-point Likert scale (Table 3–3)
Wom	Word of mouth	Ordinal	7-point Likert scale (Table 3–9)
IKnown	Respondents level of knowledge in online transactions	Ordinal	1-4 (Novice to expert)
PRiskSum	Perception of Risk	Ordinal	7-point Likert scale (Table 3–7)
TrustSum	Security perception during the transaction process	Ordinal	7-point Likert scale (Table 3–6)
	(Other variables)		
Phishing	Knowledge about identity fraud on internet	Ordinal	0-1 No - Yes
Trust3	"In general, I do not trust the purchasing process in the web site as much as I trust traditional purchasing processes"	Ordinal	7-point Likert scale (Table 3–6)
Skill	Expertise level in internet operations	Ordinal	1-4 Novice to Expert

Continued on next page...

Table 4–1 ... continued from previous page

Predictor Name	Description	Type	Scale
IB8	I avoid buying things that are not on my shopping list.	Ordinal	7-point Likert scale (Table 3–4)
Hours	Hours per week spent on computer	Ordinal	less than 5 5 - 10 10 - 20 more than 20
PRisk1	Risk tolerance when deciding to make a purchase from the web sites	Ordinal	7-point Likert scale (Table 3–7)
PRisk2	Overall perception of risk from a web site	Ordinal	7-point Likert scale (Table 3–7)

Table 4–2: Dependent variables

Variable name	**Description**	**Type**	**Scale**
TimeScal	Number of purchases made on line (last six months)	Ordinal	None Low Medium High
SpendSca	Amount of money spent in online purchases (last six months)	Ordinal	None Low Medium High

We used Answer Tree 3.0 as a computer learning system to create the classification displayed in the form of decision trees. Exhaustive CHAID was selected as the growing method for the decision trees. Exhaustive CHAID is a modification of CHAID (CHi-squared Automatic Interaction Detector) algorithm which is an efficient statistical technique for segmentation, or tree growing [56]. CHAID, evaluates all of the values of a potential predictor variable. It merges values that are judged to be statistically homogenous with respect to the target variable and maintains all other values that are heterogeneous. Exclusive CHAID examines the series of merges for the predictor and finds the set of categories that gives the strongest association with the target variable, and computes an adjusted p-value for that association [39].

The exhaustive CHAID algorithm follows the following steps [57]:

1. For each predictor variable X, find the pair of categories of X that is least significantly different (that is, has the largest p-value) with respect to the target variable Y.

2. Since our target variables (Y's) are ordinal, the Chi-Square statistic is calculated using the likelihood ratio statistic. The null hypothesis of independence of X and Y is tested against the row effects model (with the rows being the categories of X and columns the classes of Y) proposed by Goodman [58]. Two sets of expected cell frequencies, $\hat{m}_{ij}$ (under the hypothesis of independence) and $\hat{\hat{m}}_{ij}$ (under the hypothesis that the data follow a row effects model), are both estimated. The likelihood ratio statistic (H^2) and the p-value (p) are calculated by the following equations (4.1 and 4.2).

$$H^2 = 2\sum_{i=1}^{I}\sum_{j=1}^{J}\hat{m}_{ij}ln(\hat{m}_{ij}/\hat{\hat{m}}_{ij}) \tag{4.1}$$

Where:

$J = categories\ of\ the\ target\ variable\ (Y)\ and$

$I = categories\ of\ the\ current\ independent\ variable\ (X)$

$$p = Pr(X^2_{i-1} > H^2) \tag{4.2}$$

3. The pair having the largest p-value is merged into a compount category.

4. Calculate the p-value based on the new set of categories of X.

5. Repeat steps 1, 2 and 3 until only two categories remain. Then, among all sets of categories of X, find the one for which theh p-value in step 3 is the smallest.

6. Compute the Bonoferroni adjusted p-value for the set of categories of X and the categories of Y.

7. Select the predictor variable X that has the smallest adjusted p-value (the one that is most significant). Compare its p-value to a prespecified alpha level (α_split). The alpha level for spliting in this procedure was stablished at 0.05.
   - If the p-value is less than or equal to (α_split, split the node based on the set of categories of X.
   - If the p-value is greater than (α_split, do not split the node. The node is a termianal node.
8. Continue the tree-growing process until the stopping rules are met.

4.2 Validating the tree

For validating the classification trees, Partition Data methodology was selected. For this purpose, the sample was separated in two sets, a training sample and a testing sample. The training sample was composed of 64.6% of the data (nTraining = 485) while the test sample gets 35.4% of the data (nTest=266). After a model has been processed by using the training set, the model is tested by making predictions against the test set. Because the data in the testing set already contains known values for the attribute that we select as dependent variable, it was straightforward to determine whether the model's predictions are correct.

4.3 Segmentation analysis

The selected target variables were analyzed individually, considering first the number of purchases made on line (TimeScal) as the target variable and then the money spent on online purchases in the last six months (SpendScal).

4.3.1 First segmentation

For this first segmentation, we used "TimeScal" as the target variable. In doing so, we first considered the group of socio-economic variables as the predictors for the target variable. We wanted to observe if only with this group of variables we can achieve a good classification scheme. Also, we could see which are the best predictors in forming of purchase intention taking into account the socio-economic characteristisc of the consumers.

Based on this group of predictors, the resulting tree contains eight terminal nodes as we can see in Figure 4–1.

The algorithm selects the predictor Age as the best predictor in this group of variables (Chi-square =32.9303, p-value= 0.0000). The sample was separated into two classes of consumers: People from 21-33 years old and people from 16-20, 34 or more.

For a brief interpretation of this tree, we can observe the terminal nodes. For example node 20 and 21 correspond to consumers who are from 21-33 years old, having a budget up to \$300. In these cases 29.55% of females would never buy online, while in the case of male the proportion is 20.59%. We can observe that as the level of the predictor variable "Budget" increases, the proportion of consumer who do not buy online decrease. In nodes 15 and 16, this rate decrease to 17.14% and 11.11% respectively.

On the other side, terminal nodes 24 and 25 represent consumers at the ages of 16-20,34 or more, having a budget ranging from \$100 to \$200. Looking at these

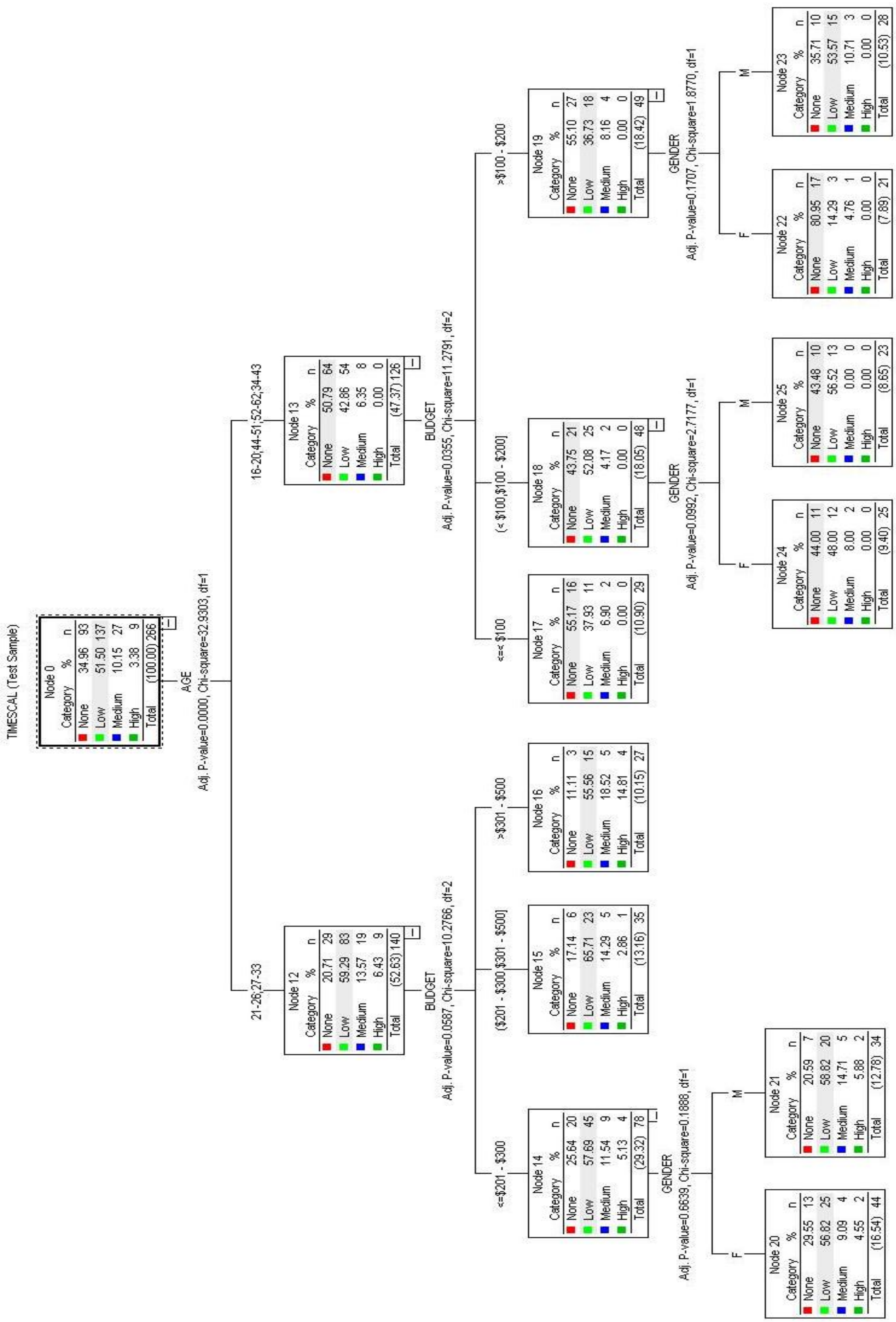


Figure 4–1: First segmentation. Target Variable: "TimeScal". Predictors: Socio-economics variables)

nodes, the proportion of non buyers is 44% for females and 43.48% for males. However, contradictory, as the level of “Budget” increase, the proportion of nonbuyers also increase. In terminal nodes 22 and 23 we can observe that 80.95% of females do not buy online, while 35.71% of males falls in this category.

With these results we can see that we need to consider other variables to better explain better the segmentation. Examining the risk estimate reinforces this conclusion. The risk estimate with socio-economic variables is 0.4285. This means that we will classify 57.15% of cases correctly (Table 4–3).

Table 4–3: Risk Summary. Target variable: “TimeScal”, Predictors:Socio-economics variables

—	Risk Statistics
Risk Estimate	0.428571
SE of Risk Estimate	0.0303425

From the whole group of independent variables (including socio-economics variables), the resulting tree contains eleven terminal nodes as we can see in Figure 4–2. For analysing this tree we can observe some terminal nodes to explain this segmentation.

Looking at terminal nodes 8 and 9 representing consumers in the middel level of “Wom4” (neutral to reviews presented on the website, see description on Table 4–4) we can observe the results of the classification process. In these cases, when the level of “IKnowns” is less than “Advanced”, the nonbuyers represent a 64% of this type of consumers. It is interesting that an increment in the level of “IKnowns” reduced the proportion of nonbuyers in almost a half, in this case to 28.95% (node 38).

Other interesting findings could be observed in terminal nodes 14 and 15. Those nodes, represent consumers with a level of “Wom4” equals to 5 (agree somewhat) and ages ranging from 21 to 43 years old. When the level of “TrustSum” is below 8 (little

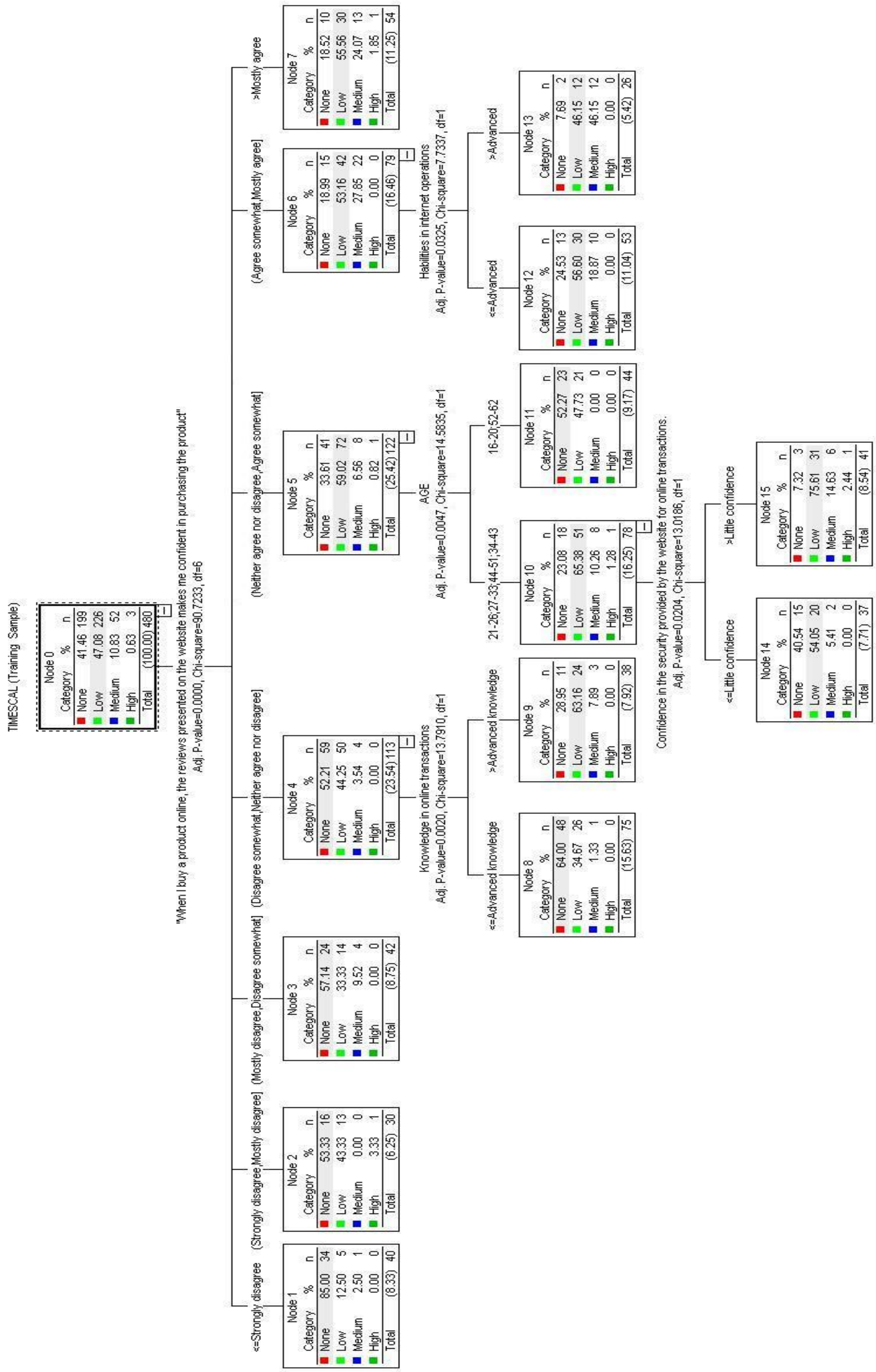


Figure 4–2: First segmentation. Target Variable: "TimeScal", Predictors: all variables

confidence in online purchases), the proportion of nonbuyers results in 40.54% while if the level of "TrustSum" is greater than 8 the proportion of nonbuyers is 7.32%. Similary observing terminal nodes 12 and 13, in this case consumers with a higher level of "Wom4" (mostly agree), nonbuyers proportion are reduced from 24.57% to 7.69% by incrementing the level of "Skill" (habilities in internet operations).

Exhaustive CHAID selected only five variables as predictors for the dependent variable "TimeScal" (Table 4–2). CHAID selected those variables that best discriminate respondents in the dependent variable. The best predictor for the dependent variable is the variable having the high value in the Chi-Square statistic test [56].

Table 4–4: Best predictors for "TimeScal"

Variable	Description	Chi-Square	p-value
Wom4	"When I buy a product online, the reviews presented on the website make me confident in purchasing the product"	90.7233	0.0000
IKnown	Respondents level of knowledge in online transactions	13.7910	0.0020
Age	Age of the respondents grouped in six cohorts.	14.5835	0.0047
Skill	Expertise level internet operations	7.7337	0.0325
TrustSum	Security perceptions during the transaction process with a web retailer.	13.0186	0.0204

We performed the risk summary of the resulting classification in order to find out what proportion of cases is incorrectly classified (Table 4–5). The risk summary shows that the current tree classifies almost 61% of the cases accurately (4% more than when using only socio-economics variables).

Table 4–5: Risk Summary. Target Variable: "TimeScal" - all predictors

—	Risk Statistics
Risk Estimate	0.390977
SE of Risk Estimate	0.0299193

4.3.2 Second segmentation

In this case we used money spent on online purchases as the target variable.

For all the predictors, Exhaustive CHAID selected again variable Wom4 as the best predictor. However, variable Age is not longer a good predictor for "SpendScal". Instead, the persuasive power, personal budget and his/her knowledge level on online transactions better predict the target variable. Figure 4–3 shows the decision tree with ten terminal nodes. Table 4–6 presents the predictors for "SpendScal" variable.

The first level of the tree shows three branches representing respondents' level of variable "Wom4", with the terminal node 1 representing consumers who strongly disagree with the statament *"When I buy a product online, the reviews presented on the website make me confident in purchasing the product"*. The percentage of non-buyers is really significant (85%). It was further noted that as the level of "Wom4" increases, the proportion of nonbuyers decreases to 25.88% (node 41 represent people who agree with the statement in variable "Wom4").

Terminal node 24 represents consumer who are neutral or disagree with the statement in variable "Wom4" and also having low knowledge in online transactions, the nonbuyers percentage in this segment 64.06%, decreasing to 29.82% when the level of IKnows increases.

In terminal node 26 we observe that the variable "Trust3" is determinant in the proportion of nonbuyers. Consumer who are neutral or disagree with the statement "In general, I do not trust the purchasing process in the web site as much as I trust traditional purchasing processes" having a superior level in online transactions are more likely to buy online (nonbuyers=10%), while people disagreeing with the statement in "Trust3" have a lower rate of purchase probability (nonbuyers = 51.85%) despite their expertise in online transactions.

Terminal node 30 represents consumers that agree with the statement for the predictor variable "Wom4" and having confidence in online purchasing process but

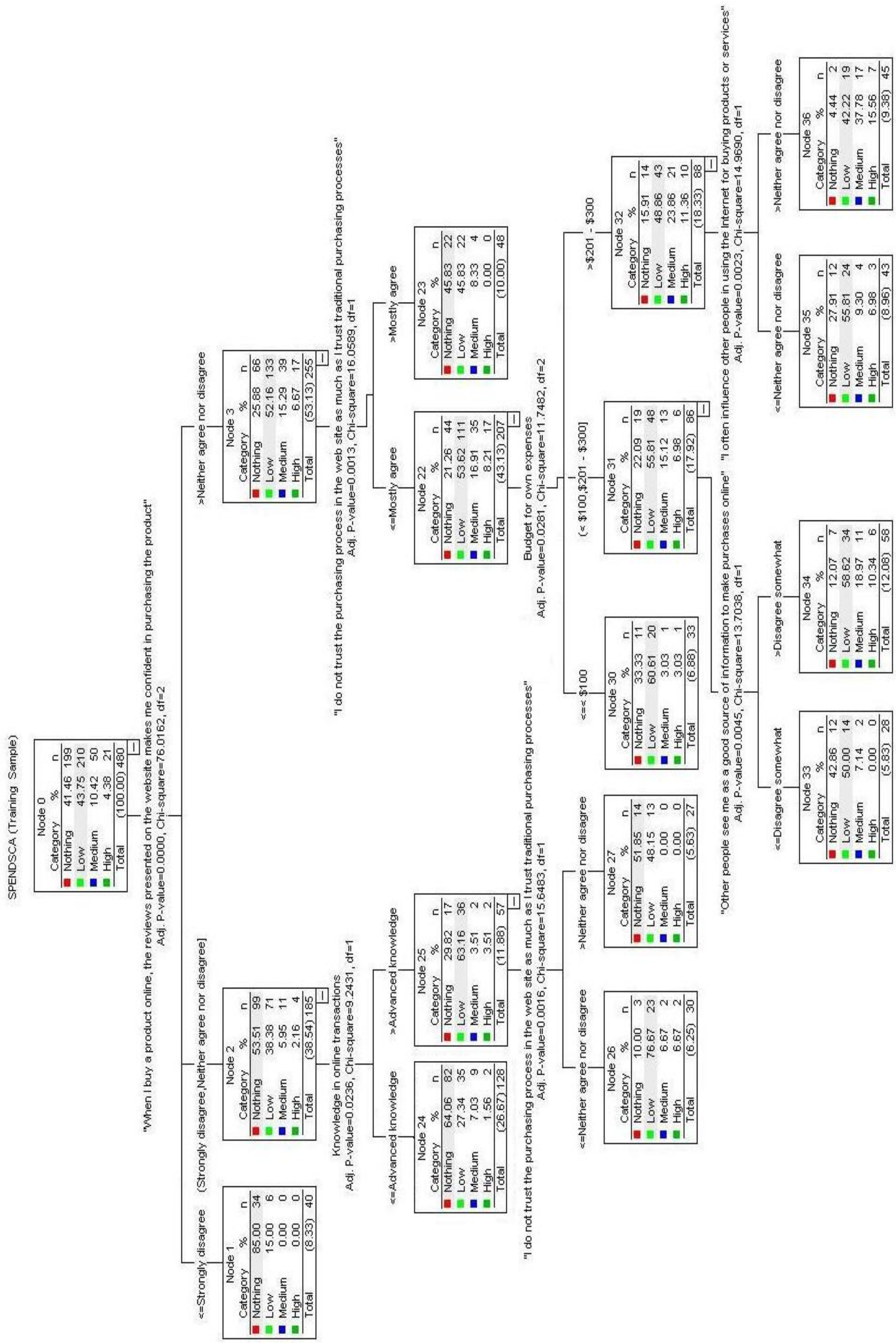


Figure 4–3: Second segmentation. Target Variable: SpendScal, Predictors: all variables

with low budget for own expenses (less than \$100). Due to this low number, the percentage of nonbuyers is 33.33%. This will be decreased to 15.91% if the level of "budget" increases.

Finally, terminal nodes 33 and 34, represent people with all the characteristics described above and split according to the level of agreement with the statement "Other people see me as a good source of information to make purchases on the Internet" (Wom2). People who disagree with that statement has a nonbuyer representation of 42.86%, whereas in the other case the percentage decrease to 12.07%. Similary terminal nodes 35 and 36, represent people having a "budget" more than \$300. In particular terminal node 53 represents people who disagree with the statement in variable "Wom1" ("I often influence other people in using the Internet for buying products or services"). The percentage of nonbuyers in this case is 27.91% which is reduced to 4.44% in the segment represented by people who agree with the statement in predictor "Wom1".

Table 4–6: Best predictor for "SpendScal"

Variable	Description	Chi-Square	p-value
Wom4	"When I buy a product online, the reviews presented on the website make me confident in purchasing the product"	76.016	0.0000
Trust3	"In general, I do not trust the purchasing process in the web site as much as I trust traditional purchasing processes"	16.0589	0.0013
Wom1	I often influence other people in using the Internet for buying products or services	14.9690	0.0023
Wom2	Other people see me as a good source of information to make purchases on the Internet respectively	13.7038	0.0045
Budget	Personal budget for own expenses	11.7482	0.0281
IKnown	Respondents level of knowledge in online transactions	9.2431	0.0236

4.4 Consumer's classification and decision rules

As a result of the above analysis, profiles of consumers were generated as we can see in Table 4–7. It also shows the decision rules for each profile shown in the table.

Based on the classification tree for each dependent variable (Table 4–2), the goodness of the segmentation can be evaluated by the comparison of the response rate of the whole sample and the response rate of the terminal nodes [59]. Therefore a response index was created for the best three terminal nodes to clarify the gains of addressing selected subgroups instead of addressing the sample. Everyone of the profiles presented in Table 4–2 are characterized by having higher response rates than the average.

Table 4–7: Consumer's classification and decision rules

Profile	**Node**	**Resp %**	**Index %**	**Likelihood %**	**Decision rule**
People who never make an online purchase					
1	1	85	268.1	85	WOM4 = 1 People who have no confidence in the reviews presented in a web site
2	8	64	158.2	64	WOM4 = 4 and IKnown $\leq$ 2 People who are neutral to the reviews presented in a web site but do not have sufficient knowledge on internet transactions
3	11	52.27	107.3	52.27	WOM4 = 5 and age between 16-20 or above 52
People who make at least one purchase online					
4	15	75.61	151	75.61	WOM4 = 5 and age between 21 - 52 and TrustSum > 8 People from 21 to 52 years old who feels confident in the reviews presented in a web site and also have an acceptable security perception during the transaction process.
5	13	46.15	135	46.15	WOM4=6 and Skill > 3 People who feels very confident in the reviews presented in a web site and have advanced abilities in internet operations
6	9	63.15	114.2	63.15	WOM4 = 4 and IKnown >2 People who are neutral to the reviews presented in a web site and have sufficient knowledge on internet transactions.

Continued on next page...

Table 4–7 ... continued from previous page

Profile	**Node**	**Resp%**	**Index %**	**Likelihood%**	**Decision rule**
People who does not spend money purchasing online					
7	1	85	268.1	85	WOM4 = 1 People who have no confidence in the reviews presented in a web site
8	24	64.06	171.6	64.06	WOM4 > 1 and WOM4 ≤4 and IKnown≤2 People who are neutral or are not confident to the reviews presented in a web site and do not have the sufficient knowledge on internet transactions
9	27	51.85	78	51.85	WOM4 > 1 and WOM4 ≥ 4 and IKnown > 2 AND Trust3 > 4 People who are neutral or are not confident to the reviews presented in a web site and have sufficient knowledge on internet transactions but do not really trust in the online purchasing process.
People who does spend some money purchasing online					
10	26	76.67	155.2	76.67	WOM4 > 1 and WOM4 ≤ 4 and IKnown > 2 AND Trust3 ≤ 4 People who are neutral or are not confident to the reviews presented in a web site, having sufficient knowledge on internet transactions and really trust in the online purchasing process.
11	35	55.81	141.1	55.81	WOM4 > 4 Trust3 ≤6 Budget > $300 and WOM1 ≤ 4 People who are confident to the reviews presented in a web site, having a budget > $300 but with less probabilities to influence someone to buy online.
12	34	58.62	127.3	58.62	WOM4 > 4 and Trust3 ≤ 6 and Budget ≤3 and WOM2 > 3 People who are confident to the reviews presented in a web site, having a budget < $300 with some probability to influence someone to buy online.

CHAPTER 5
MULTI-AGENT BASED MODEL

The prior literature reviewed shows that modeling an ABM is a complex process. This complexity is because an ABM model requires capturing the changing behavior and interactions between all the components in the system. The main idea in developing an ABM is to specify the rules of behavior for individual entities, as well as the rules of their interaction. Using a computer model, this procedure is done in order to simulate a multitude of the individual entities and then explore the consequences that the rules specified at the individual level will have on the entire population of agents as a whole.

In an ABM, entities are called "agents" and the simulation of their interactions is known as agent-based simulation.

There are several methodologies for developing an ABM. Some authors tried to adapt previous agent based methodologies ([60], [61], [62], [63] and [64]) whereas others proposed their own style for the development of an agent based model ([8], [65] and [66]).

In particular, Macal et al. [8], developed the general steps in building up an agent-based model. We bear in mind this procedure to realize our model. A brief description of each of these stages is described below.

1. **Identify Agents:**

   Identify the agent types and other objects along the system, specifying their attributes.

Identifying agents, accurately specifying their behaviors, and appropriately representing agent interactions are the keys to developing useful agent models [8].

2. **Environment:**

   Define the environment where the agents live in and interact with.

3. **Agent Methods:**

   Specify the methods by which agent attributes are updated in response to either agent to agent interactions or agent interactions with the environment.

4. **Agent Interactions:**

   Add the methods that control which agents interact, when they interact, and how they interact during the simulation.

5. **Implementation:**

   Implement the agent model in an ABM simulation tool.

We can organize the above steps in order to include them in the general development system process model. Therefore developing an agent based simulation is part of a more general development process (Figure 5–1).

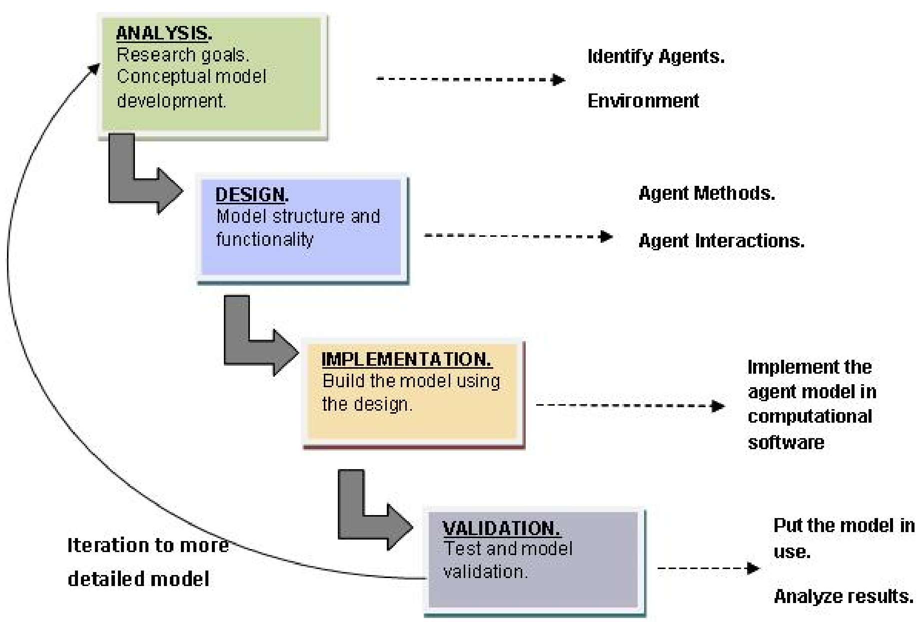


Figure 5–1: Agent Based Simulation lifecycle

5.1 Identification of agents and environment

In the defined context (e-commerce) the relevant agent is characterized by the consumer who desires to purchase a product online. We called this agent the "Consumer_Agent". The environment in which agents live is the electronic commerce where a "Consumer_Agent" is looking for information to establish a purchase in order to satisfy a need.

For this research, we called the defined environment as the "Web_Environment". In this environment, many instances of "Consumer_Agent" (each one having their own behavior), are surfing the "Web_Environment" in order to find a web page to shop online and meet their needs. Also they may interact with each other for sharing information, exchanging experiences about the purchasing process.

The interaction between consumer agents occurs prior to making a final purchase decision. Each "Consumer_Agent" has to observe their surroundings and look for specific attributes in the other agents. This type of interaction may cause an agent to be influenced by others in its final decision. Those attributes corresponds to the variables that explain the Word of mouth phenomena (WOM) [36] described in Chapter 3. In this case each "Consumer_Agent" takes into account those values as a reference of the persuasive power the surrounding agents have toward him.

We also defined another type of agent in our model, the web site. The web site is considered an agent since it represents the external influence on consumer behavior due to the environment. The agent called "Web_site" interacts with the "Consumer_Agent" each time it is faced with the decision to make a purchase online. The interaction in this case occurs due to the consumer's perception in the reviews presented in the web site. This property was defined in chapter 3 ("WOM4") as a variable that influences online consumer behavior. Morover, this fact was proven in Chapter 4 where "WOM4" results the best predictor of consumer behavior in the two dependend variables defined in the same Chapter. Therefore, the agent "Web_Site" sends a message telling the “Consumer_Agent” how successful prior purchases were made on it. The “Consumer_Agent” perceives the message and searches internaly the level of influence the reviews presented in the web site has on his final purchase decision (WOM4).

Table 5–1 sumarizes the two types of agents identified which were defined in the ABM for consumer behavior.

Table 5–1: Agents Identified for the Consumer behavior ABM

Name	**Description**	**Type**	**Interactions**
Consumer_Agent	An online consumer who surf the web in order to buy a product	Animate	Consumer to Consumer, Consumer to website
Website_Agent	A web site where the consumer purchases online	Inanimate	Website to consumer

Under this scheme (Figure 5–2), the agents inhabit the environment taking into account their own decision rules extracted from the classification tree analysis in Chapter 4. All this information have to be included in the interaction and in the adaptation process.

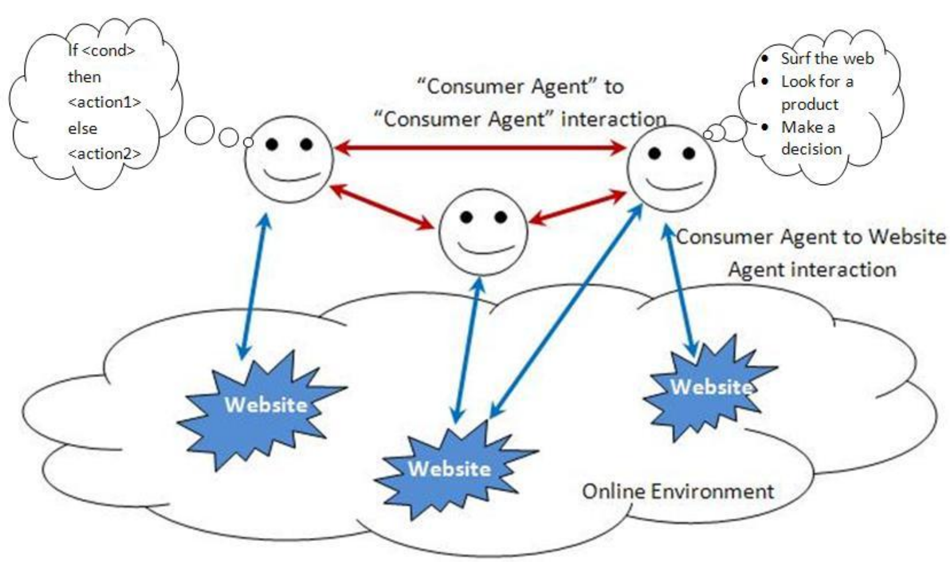


Figure 5–2: Agents, enviroment and interactions

5.1.1 Model's Limitations

There are some limitations to take into consideration prior to describe the agent's architecture and the implementacion of the simulation model. These limitations exist due to the complexity of representing a model that captures all aspects of real e-commerce. In this model we have only represented the consumers who browse several web pages without any preference of type or product offered.

The "Website_Agent" represents a website in general, we did not take into account some characteristics of a real website such as content, ease of use, type of product and prices. That means a "Consumer_Agent" navigates through web pages randomly without having certain preferences.

The website-consumer interaction is based only on the positive reviews that appear on the website. The "Consumer_Agent" calculates it purchase probability based on that the "Web_site" agent positive reviews only.

Since the "Website_Agent" lacks the attributes described above, the "Consumer_Agent" observes if there are positive reviews on the website without discriminating whether these relate to the product ofered or reviews of the website itself.

Consumers do not take into account previous buying experiences, i.e. at every instant in the simulation his/her decision is based only on the two types of interactions described above and the decision rules derived from the classification tree analysis described in Chapter Four (Figure 4–2).

Finally, the number of agents is represented by a fixed number that is maintained throughout the simulation, i.e. there are no new "Consumer_Agent" created representing an entrance to the internet shopping environment neither a represetation of the destruction of agents.

5.1.2 Agent's architecture

In ABM agents are commonly implemented in a software tool and defined as software objects possesing properties (instance variables) and associated rules of behavior (methods). Utilizing object oriented methodology, the properties and the rules of behavior for an agent can be implemented as public and private. Mehta and Bhattacharyya [24] developed a software structure of an agent (in pseudo-code) that could be used to implement it in a software platform for scientific agent-based models. In this general structure we can observe the following components:

Private properties are those variables that are inherent only to a particular agent and can changes internally. By contrast, public properties are those that can generate or receive influences from the interaction with other agents and thus change the status and the behavior of a particular agent.

Similarly there are private and public methods in which private methods are those that are perceptible only by an agent in particular and the public method can be perceived by other agents.

The general structure of "Consumer_Agent" is presented in Figure 5–3. Since only the "Consumer_Agent" is modeled as "animate", it is able to act autonomously and interact with other agents, while the "Web_site" agent is modeled as "inanimate" since it lacks the capacity to initiate and interaction with other agents. Figure 5–4 presents the general structure of "Website_Agent".

Generally, when designing the ABM, the rules of behavior are represented in an ABM simulation language as if-then-else sentences. The ABM simulation language interprets and represents the behavior of the agents. Influences and interactions with other agents are represented by the same rules as well. The next section explains in detail the methods defined for every agent identified in our model. Note that "Website_Agent" does not have neither public nor private methods since it was defined as an "inanimate" agent.

```
Consumer Agent: {
   private properties:
   //Socio-economic characteristics
   Gender;
   Age;
   Work Stus;
   Student;
   Ed level;
   Famincome;
   Budget;
   // Internet Skills;
   Hours;
   Skill;
   Hours;
   Phishing;
   PRisk1;
   PRisk2;
   // Knowledge in online transactions
   IKnown;
   // Perception of risk
   Disposition to trust;
   // Impulsive behavior
   ImpBvior;
   Imp8;
   // Security perceptions
   Trust;
   TrustSum;
   // Self Efficacy
   SelfE;
   // Word of mouth
   WOM1;
   WOM2;
   WOM3;
   WOM4;
   WOM5;
   public properties:
   WOM4;
   Times;
   Spend;
   private methods:
   Surf the web; // the agent moves around the web environment
   Look around; // the agent looks around for other agents
   Evaluate following decision;// the agent evaluates next decision
   according to his behavioral rules
   public methods:
   Purchase decision; // to buy or not to buy in the actual web site
}
```

Figure 5–3: "Consumer_Agent" architecture

```
Website_Agent {
    private properties:
    Score; //website score according to its reviews (Very Low .. Very
    High)
    public properties:
    CountReviews; //Number of web site positive reviews
    private methods:
    public methods:
}
```

Figure 5–4: "Website_Agent" architecture

5.2 Agent methods

The agent methods specify the logic by wich agent attributes are updated in response to either agent-to-agent interactions or agent-website interaction.

According to the GAIA methodology (a methodology for agent-oriented analysis and design) proposed by Wooldridge et al. [63], an agent-based system is represented in a hierarchic form (Figure 5–5): The first level is represented by the agents while the second level represents the methods as roles played by each type of agent.

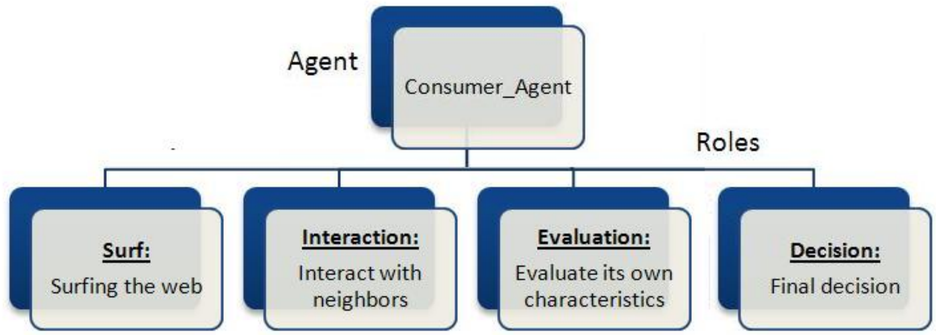


Figure 5–5: Consumer-Agent roles

The agent model consists on a set of agents and roles which are described individually. Each element in the agent model gets specific information about its own state including its relations with other agents.

To precisely define the roles, we used the GAIA roles model [63]. A roles model is comprised of a set of role schemata (Table 5–2), one for each role in the system. A role schema draws together the various attributes discussed in the previous section into a single place. In those schemas we represented different aspects that characterize the two agents defined. In this case we described the methods by which agent attributes are updated in responde to either agent-to-agent interactions or agent interaction with the environment.

Table 5–2: Template for Role schemata. GAIA metodology

Role Schema	**Name of role**
Description	*Short description of the role.*
Protocols and activities	*Protocols and activities in which the role plays a part.*
Permissions	*"Rights" associated with the role.*
Responsibilities	*The main objectives to be met.*

At each time period, during its participation in the online purchasing process, the consumers undertakes actions according to the current state and decide the state for playing a role in the next period. Figure 5–5 shows the four roles identified for the "Consumer_Agent" to be performed in each time period. Note that the "Website_Agent" does not have any role defined since this agent is considered inanimate.

Depending on the role played, the "Consumer_Agent" obtains the necessary information to excecute actions for that role and for deciding on the state to assume in the next time period. This is determined by the rules of behavior obtained in Chapter Four (Figure 4–2) and the interactions between agents, which are discussed in the next section. The dependences on each own behavioral rules allows each consumer to act individually, obtaining and processing different information in each time period. In a given time period two "Consumer_Agents" can decide their actions differently owing to differences in their attribute values such as the defined in Chapter 3.

5.2.1 Consumer_Agent Role: Surf the web

For each time period a "Consumer_Agent" surfs the web in order to visit the web sites located throughout the web environment. By this role the "Consumer_Agent" looks for information about the reviews presented in every web site visited.

As described in the architecture of agents, the "Website_Agent" has two properties indicating the level of acceptance of the website. "CountReviews" property stores the amount of positive reviews a web site has and "level" property represents the acceptance level the website has in conducting online transactions.

These values are to be read and stored internally in the agent for later use. Until this moment, the agent has not taken any decision or changed the values of their properties. Its status in this role is "surfing".

Table 5–3: Consumer_Agent Role: SURF THE WEB

Role Schema: SURF THE WEB
Description: A "Consumer_Agent" moves through the web visiting websites with the aim of buying a product and meet its needs.
Protocols and activities: Move around and observe web site parameters
Permissions reads website.CountReviews //*number of positive reviews in the web site* reads website.Score //*website score according to its reviews (Very Low .. Very High)* write state = surfing //*agent state is now surfing*
Responsibilities Get the number of positive reviews in the web site . Get the score level of the web site. Keep both parameters internaly for future tasks. Set state = surfing

5.2.2 Consumer_Agent Role: Observe neighbors

While a ("Consumer_Agents") surfs the web, other agents of the same type are also performing the same action. This environment is feasible for the ocurrence of the phenomena called the of word of mouth among consumers [36]. For this purpose, the agent must determine the degree of influence of the surrounding agents near to him/her. The objetive of this role is to measure the persuasive power exerted by the neighboring agents. In Chapter 3 we defined the variables dealing with this phenomena.

By executing this role, the "Consumer_Agent" gets information about the persuasion level exerted by its neighbors, specifically, the values of the properties "wom1" and "wom2" (Table 3–9). High values in those properties show that the neighboring agents have a high power of persuasion in the "Consumer_Agent" final decision. Along with these variables, the "Consumer_Agent" must obtain current information about the success of neighbors online purchases. The value of this propery is obtained from the variable "Times". A high value in this property means that the neighbor agent made successful purchases. A value of zero indicates the opposite.

This information is read and stored in the knowledge base of the "Consumer_Agent" and is useful for making its final decision under the behavioral rules.

Table 5–4: Consumer_Agent Role: OBSERVE NEIGHBORS

Role Schema: OBSERVE NEIGHBORS
Description: The "Consumer_Agent" begins to look around in order to get information from their neighbors. This informacion may influence in their final decision.
Protocols and activities: Select a group of consumer agents near him. Obtain relevant properties
Permissions reads Consumer_Agent.Times //*number of succesful purchases in the web site* write state = observing //*agent state is now observing*
Responsibilities Get the number of succesful purchases made by other agents. Keep these parameters internaly for future tasks. Set state = observing

5.2.3 Consumer_Agent Role: Internal Evaluation

Based on its intrinsic properties, each "Consumer_Agent" has certain characteristics which will determine its subsequent behavior. Before executing the next action, a "Consumer_Agent" evaluates the state or its properties and then it is able to develop a consequente behavior.

Therefore, the responsibility of the "Consumer_Agent" is to generate a list of its current properties values. Based on those values, the next role is to determine which behavioral rules the agent will follow to complete its decision.

Table 5–5: Consumer_Agent Role: INTERNAL EVALUATION

Role Schema: INTERNAL EVALUATION
Description: The "Consumer_Agent" performs an internal inspection in order to evaluate its properties.
Protocols and activities: Generate a list of values from their own characteristics
Permissions reads Consumer_Agent.SocioEconomics //*Age, Gender, Budget* reads Consumer_Agent.Personality //*Trust, Wom3, Wom4, Wom5* reads Consumer_Agent.Knowledge //*Internet skills, online transaction knowledge* write state = Evaluating //*agent state is now evaluating*
Responsibilities Store values of internal properties. Keep these parameters internaly for future tasks. Set state = Evaluating

5.2.4 Consumer_Agent Role: DECISION

This role describes the "Consumer_Agent" reponsibility in evaluating its behavioral rules according to its intrinsic and extrinsic factors. This procedure is based on the consumer profiles studied in Chapter Four where it was defined the decision rules. According to the Consumer_Agent profile, the probality of belonging to one of the buyers categories, i.e non buyers, low buyers, medium buyers or high buyers is determined. Once the Consumer_Agent is classified, it is determined the number of purchases to be made in the actual web site, where the Consumer_Agent is located. For example, if the agent is a nonbuyer then, the number of purchases will be zero, otherwise if it is a low buyer, the number of purchases will be between 1 and 5 and so on.

Finally, according to the number of purchases, the Consumer_Agent puts reviews in the web site. Those reviews are stored in the Web_Agent in its property "countReviews", allowing other "Consumer_Agents" to see this value in the next simulation time period.

Table 5–6: Consumer_Agent Role: DECISION

Role Schema: DECISION
Description: The "Consumer_Agent" follows its own rules of behavior according to the parameters stored.
Protocols and activities: Calculate the willingness of wheather or not to buy online following the decision rules. Determine the number of purchases to be made
Permissions read Consumer_Agent.desicionRules write Consumer_Agent.Times //*number of online purchases* write Consumer_Agent.TimesScal //*None, Low, medium, high* write Website_Agent.countReviews write state = Deciding //*agent state is now refining*
Responsibilities Calculate willingness to buy. Calcultate the number of purchases. Set state = Deciding

5.3 Agent interactions

The interaction process is formally defined following the recommendations of the GAIA methodology [63]. The description of the interactions consists on the following statements:

- *Purpose:* brief textual description of the nature of the interaction (e.g., information request, schedule activity and assign task).
- *initiator:* the agent(s) responsible for starting the interaction.
- *Responder:* the agent(s) with which the initiator interacts.
- *inputs:* information used by the agent initiator while enacting the interaction.
- *outputs:* information supplied by/to the protocol responder during the course of the interaction;
- *processing:* brief textual description of any processing the protocol initiator performs during the course of the interaction.

Two types of interaction were identified for the ABM simulation. "Consumer to Consumer" interaction and "Consumer to Web site" interaction.

For representing the interaction process, the following sets were defined:

$$C = \{c_{ij}\}\,,\ \text{“}Consumer\_Agents\text{” } in\ the\ web\ environment, \tag{5.1}$$

$$c_{ij} = \text{“}Consumer\_Agent\text{” } having\ a\ position\ [i,j]\ in\ the\ web\ environment, \tag{5.2}$$

$$N = \{n_{kl}\}\,, \text{“}Consumer\_Agents\text{” } Neighbors, N \subset C \tag{5.3}$$

$$n_{kl} = \text{“}Consumer\_Agents\text{” } Neighbors\ at\ positon\ [i,j] \tag{5.4}$$

$$where\ i-2 < k < i+2,\ j-2 < l < j+2, \tag{5.5}$$

$$W = \{w_{ij}\}\,,\ \text{“}Website\_Agents\text{” } in\ the\ web\ environment, \tag{5.6}$$

$$w_{ij} = \text{“}Website\_Agent\text{” } at\ position\ [i,j]\ in\ the\ web\ environment, \tag{5.7}$$

5.3.1 “Consumer_Agent” to “Consumer_Agent” interaction

- *Purpose:* The purpose is to simulate the influence exerted by sorrounding agents in the current “Consumer_Agent” purchase decision. By this interaction, the “Consumer_Agent” obtains information from other “Consumer_Agents” that are surfing the web with the intention to buy online. According to its properties “Wom3” and “Wom5” a “Consumer_Agent” has a likelihood to be influenced by its sorrounding “Consumer_Agents” who made successful and secure online purchases.
- *initiator:* Actual “Consumer_Agent” being evaluated.
- *Responder:* A set of neighbors **N** that sorround the agent at a given distance.
- *inputs:* Four “Consumer_Agent” properties are used as input variables for this interaction process. On the one hand, we have “Wom3” and “Wom5” variables that represent the likelihood to make an online purchase based on the succesful experiences from other agents. On the other hand, “Wom1” and “Wom2” represent the likelihood to influence others for buying online.
- *outputs:* Variable “Times” is incremented by one unit each time the consumer decide to buy online due to the interaction process.

- *processing:* This process begins defining a set of neighbors **N** for the current "Consumer_Agent" $c_{ij} \in C$

From the set **N**, only the neighbors n_{kl} having "Wom1" and "Wom2" greater than 4 (Agree somewhat to strongly agree) and Times > 0 (number of purchases > 0) are selected. Next, the probability of buying is determined taking into account the properties "Wom3" and "Wom5" of the current "Consumer_Agents". The following seudo-code ilustrates the "Consumer_Agents" to "Consumer_Agents" interaction process:

Consumer to Consumer interaction process

```
Consumer to Consumer interaction:
for each n_kl ∈ N {
    if n_kl.wom1 > 4 and n_kl.wom2 > 4 and n_kl.times > 0
          increment influential neighbors who buy online
    if there are influential neighbors
          calculate c_ij.P(Buy) based on its behavioral rules
          // P(Buy) is the probability to buy in the website
}
```

5.3.2 "Consumer_Agent" to "Website_Agent" interaction

- *Purpose:* Determine the consumer's buying likelihood by the interaction with the website."Consumer_Agent" takes into account the number of positive reviews presented in the "Website_Agent"
- *initiator:* Actual "Consumer_Agent" being evaluated.
- *Responder:* A "Website_Agent" being visited.
- *inputs:* "Consumer_Agent" "Wom4" property representing the likelihood to make an online purchase based on the reviews presented in the web site. On the other hand, "Website_Agent" "CountReviews" property representing the number of positive comments made on it.

- *outputs:* Property "Times" is incremented by one unit each time the consumer decide to buy online due to the interaction process. Property "CountReviews" is also incremented if the "Consumer_Agent" finally made a purchase on it.
- *processing:* This process start when a "Consumer_Agent" $c_{ij} \in C$ find a "Website_Agent" $w_{ij} \in W$, at the same position.

The "Consumer_Agent" c_{ij} looks for the value of the property "CountReviews" stored in the "Website_Agent". if it is found that there are positivie reviews then the probability of buying is determined by the "Consumer_Agents" decision rules. The following seudo-code ilustrates this interaction process:

Consumer to Web site interaction process

```
Consumer to Web site interaction:
if w_ij.countReviews > 0 {
    calculate c_ij.P(Buy) based on its behavioral rules
}
```

5.4 Implementation

We used Repast (Recursive Pourus Agent Simulation Tookit) Symphony for implement the simulation model. Repast is a widely used, free and open-source agent-based modeling and simulation toolkit. Originally developed by researchers at the University of Chicago and the Argonne National Laboratory, Repast is now managed by the non-profit volunteer organization ROAD (Repast Organization for Architecture and Development) and it is actually considered one of the best tools for developing social science simulations with ABM [8], [24], [26]. The Java source code was written using the Eclipse platform which is a multi-language software development platform comprising an IDE (integrated development environment).

In Repast, all user model components should be "plain old Java objects" (POJOs) with the objective that they could be accessible to and replaceable with other external software [67].

For implementing the simulacion model in Repast, we defined the following elements to represent "Consumer_Agent", "Website_Agent" and the web environment (Figure 5–6). The "Consumer_Agent" and "Website_Agent" were implemented as POJO's in Repast and named as Consumer class and Website class respectively. Appendix D shows a complete description of all the implemented clases.

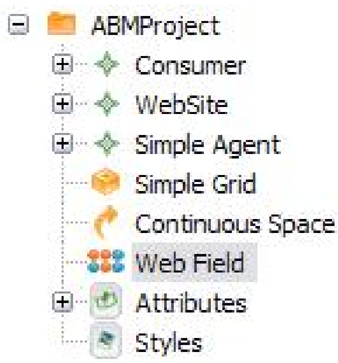


Figure 5–6: Elements in the Consumer behavior Agent Based Modeling

5.4.1 The Simple Agent

This is the general class implemented in Java, which contains common methods related to the movement and location of the two other agents. The SimpleAgent class also contains Repast-specific $\partial ScheduleMethod$ annotation, which precedes methods to be scheduled. The $\partial ScheduleMethod$ annotation has several options, including the start time and the updated interval. The SimpleAgent step method has an annotation that specifies the method to be scheduled starting at tick 1 and to recur every one tick thereafter. In this implementation of the model, the SimpleAgent class has an empty step method that was overrided by the Consumer class to specify the individual step behavior in this subclass.

5.4.2 The Consumer Class

The Consumer Class implements the "Consumer_Agent" with all the properties and methods describing the roles defined in the previous section.

```
public class SimpleAgent {
        private double heading; //angle for movement
        public double getHeading() {
          return heading;
        }
        public void setHeading(double heading) {
          this.heading = heading;
        }
        @ScheduledMethod (start = 1, interval = 1, shuffle=true)
        public void step() {
        // Overridden by subclasses
        }
...
```

Figure 5–7: Simple Agent

Along with this class, we have implemented consumer_style class to represent in colors the types of consumers according to their level of purchasing (none, low, medium, high).

```
public class ConsumerStyle extends DefaultStyle2D {
   private Color High = new Color(255, 0, 0);
   private Color Medium = new Color(174, 0, 0);
   private Color Low = new Color(117, 0, 0);
   private Color None = new Color(79, 0, 0);
...
```

Figure 5–8: Consumer_Style Class

5.4.3 The Website Class

The Website Class implements the “Website_Agent”. This class overrides the step method of SimpleAgent. It has a single constructor which asign a location for each instance of this class in a grid (implemented by the class Simple Grid). The step method simply checks the number of count reviews in each iteration and assign a level for the website according to its count reviews (none, low, medium and high).

It was also implemented a class named WebStyle to represent in different colors the level of the website according to its count reviews.

```
public class WebStyle implements ValueLayerStyle {
    protected ValueLayer layer;
    private Color High = new Color(255, 255, 0)
    private Color Medium = new Color(255, 255, 255 / 3)
    private Color Low = new Color(255, 255, 255 / 2)
    private Color None = new Color(255, 255, (int) (255 / 1.2))
...
```

Figure 5–9: Web_Style Class

5.5 The Simulation model

The following describes the multi-agent based simulation process, in particular the representation of each of the classes defined above and the generation of the input data for our simulation.

5.5.1 "Web_site Agent" representation in REPAST

The "Web_site Agent" was represented as each of the grid boxes of the class called "Grid Sample" which was defined as a 200 × 200 bidimensional grid (Figure 5–10). Therefore, 4000 web sites were generated for the simulation. Since the web site main property is the "Count reviews", it was assigned a random value for each web site.

These values were assigned randomly using a uniform distribution between 0 and 10 for each web site residing in the grid. Dark colors represent a high level of reviews in the website, while light colors means the opposite.

Figure 5–10: The website class in the multi-agent simulation

5.5.2 "Consumer_Agent" representation in REPAST

"Consumer_agents" were represented as solid circles located in a continuous space over the grid where the "Web_site agents" resides.

We used the empirical distributions, obtained from the data collected, to generate 1000 agents for this simulation. Empirical distributions of each variable can be found in Appendix C.

Each "Consumer_agent" were created with their respective intrinsic and extrinsic characteristics defined in previous chapters. The colors represent the types of buyers according to the number of purchases carried out each time they visit a website. In this case, dark colors represent the "nonbuyers" while light colors represent low, medium and high buyers respectively.

5.5.3 Simulation runs

Each iteration in the simulation represents a unit of time known as "tick". In each "tick" a "Consumer_Agent" performs all its roles starting from surfing the web, interacting with the website, interacting with its neighbors, and finally deciding to buy or not on the website.

For the next "tick" the "Consumer_agent" property "heading" is randomly updated, making the "Consumer_agent" able to move forward in the grid where the "Web_site agent" resides.

Figure 5–11, shows different states of the simulation. We can observe the changes in the website levels and also the increment of low and medium buyers (green and red circles) as the simulation is running.

Each simulation run takes 2000 "ticks". For this research it was performed sixteen runs in total in order to evaluate the results by changing the conditions of four variables to analyze the effects created by these variations in the results of the simulation particulary in the decrement of the number of non buyers. Next section

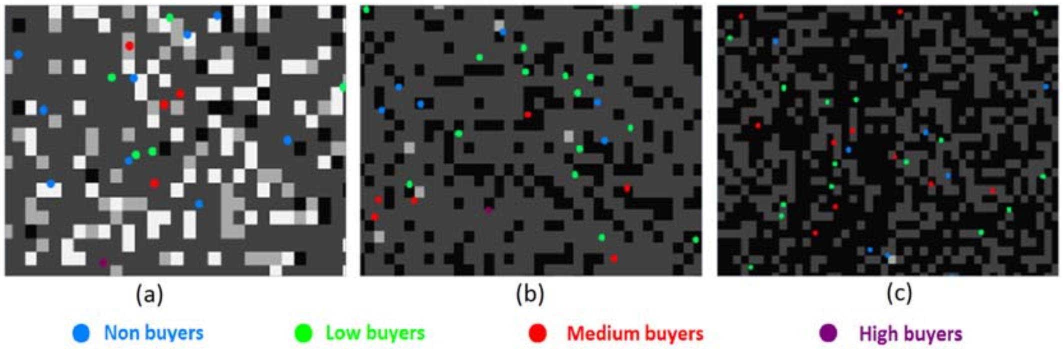


Figure 5–11: Simulation states. (a) tick 4, (b) tick 400, (c) tick 1000

formally presents the analysis and the results of the Multi-Agent based Simulation ground on an experiment that includes the four most relevant variables to predict consumer behavior, in this case for the dependent variable "Times" representing the frequency of consumers' online purchases in the last six months.

CHAPTER 6
RESULTS AND ANALYSIS

Experimentation is a vital part of the scientific method. For this purpose, after the simulation, a design of experiment was performed in order to compare different scenarios to evaluate the effect of changing four of the most significant variables in the model. A description of the experiment is presented below along with the analysis of the results obtained.

The following are the four variables that were assessed in this experiment:

- Iknown: Knowlege on internet transactions,
- TrustSum: Security perception during the online transaction process,
- Skill: Expertise level on internet operations and
- Wom4: Level of confidence in the reviews presented on the web site when purchasing a product online.

We have chosen those variables based on the results obtained from the classification tree analysis in Chapter 4. In that chapter, it was observed that an increment in one point in any of the above variables generates a change in the percentage of each type of consumer. For example, we have observed that an increment in one point in the value of the variable "Iknown" generates a reduction in the rate of non buyers and an increment in the rate of low and medium buyers. Similarly, this fact occurs when changing the values of the variables "TrustSum", "Skill" and "Wom4".

This fact generates a dynamic in the behavior of "Consumer_agents", since for each simulation time the agent properties are changing according to the increment of the four variables selected for the experiment. In this regard, whenever the agent observes an increment in the value of one of these variables, the probability to buy a product online as well as the probability of belonging to one of the four categories of buyers (i.e non buyers, low buyers, medium buyers and high buyers) changes over time.

6.1 2^4 Factorial Design

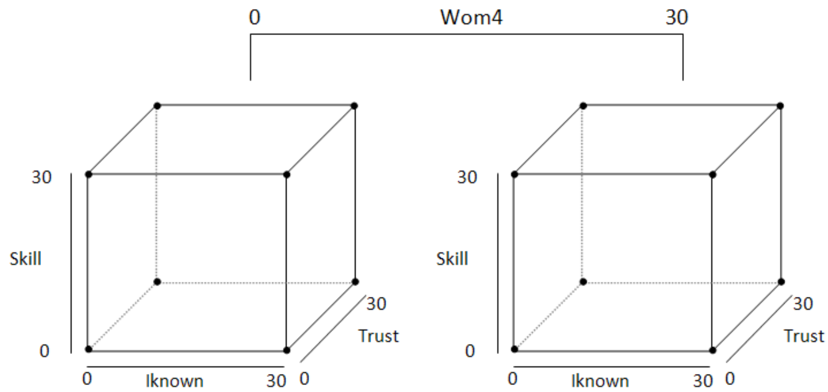
Taking into account the four variables discussed abore, it was defined a 2^4 factorial design for the experiment. In this case, we investigate the effects that those variables have in the mean number of non buyers and the contribution each factor has in reducing the rate of non buyers.

In the 2^4 factorial design defined, each of the selected variables has two levels. The low level represents no increment in the variable value. The high level represents an increment of one point in the value of the variable, represented by the rate of increment in each simulation "tick". For example one could say that every 30 ticks, the variable "Iknown" will increase one point on its actual value.

Figure 6–1 represents the 2^4 factorial design, and the sixteen treatments combinations displayed geometrically as a cube. Figure 6–1 also shows the matrix notation (design matrix) for the sixteen runs carried out.

The results of the sixteen simulation runs are shown in Figures 6–2, 6–3, 6–4 and 6–5. The graphs help us in understanding the contribution and impact of each variable on the general results. For each run we can see the change over time in the number of consumers belonging to each of the four categories of buyers (non buyers, low buyers, medium buyers and high buyers), where the "X" axis represents the simulation time measured in "ticks" and the "Y" axis represents the number of consumers for each of the four categories.

The results from the simulation runs also shows that the number of consumers belonging to each category was changing as the simulation time was increased. In general, it appears that the increment in the value of the variables considered as



(a) Geometric view

Variable				
Run	**Iknown**	**Skill**	**Trust**	**Wom4**
1	0	0	0	0
2	30	0	0	0
3	0	30	0	0
4	30	30	0	0
5	0	0	30	0
6	30	0	30	0
7	0	30	30	0
8	30	30	30	0
9	0	0	0	30
10	30	0	0	30
11	0	30	0	30
12	30	30	0	30
13	0	0	30	30
14	30	0	30	30
15	0	30	30	30
16	30	30	30	30

(b) The design matrix

Figure 6–1: The 2^4 factorial design.

factors for this experiment generates a decrement in the number of non buyers and also an increment in the number of low and medium buyers. This fact further confirms that the simulation model is consistent with the results obtained in the classification tree analysis.

A first view at Figure 6–2 shows that for high levels of “Iknown”, the decrement in the number of non buyers and also the increment in the number of low and medium buyers is greater when there is no increment in this variable (low level of Iknown, runs 1 and 3). Figure 6–2 also shows that the variable representing the habilities in performing online operations (“Skill”) has little contribution to the decreament in

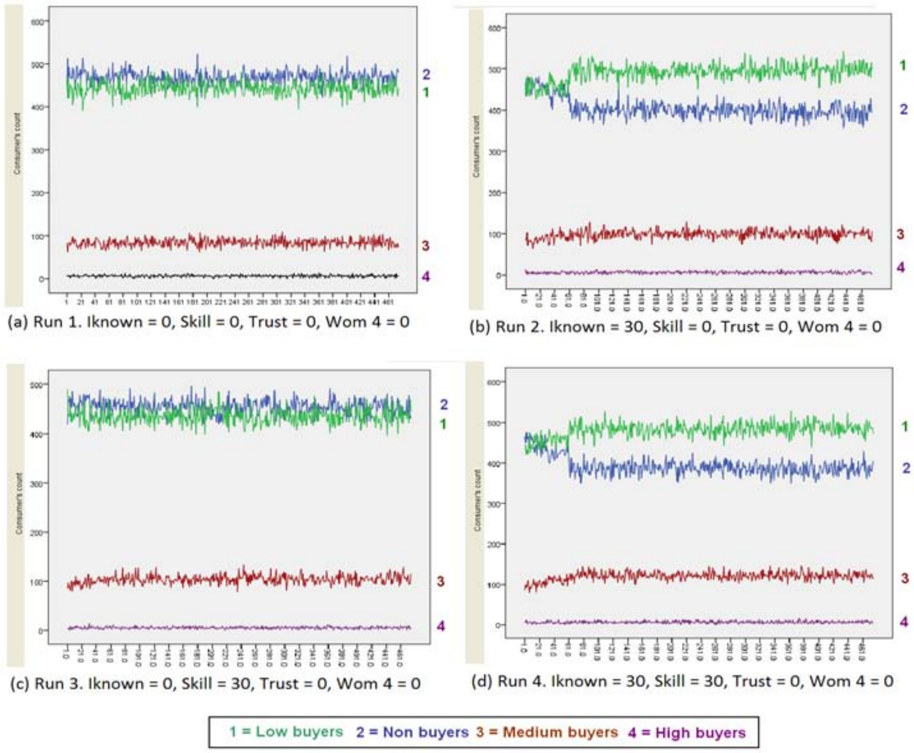


Figure 6–2: Runs 1 to 4. 2^4 factorial design

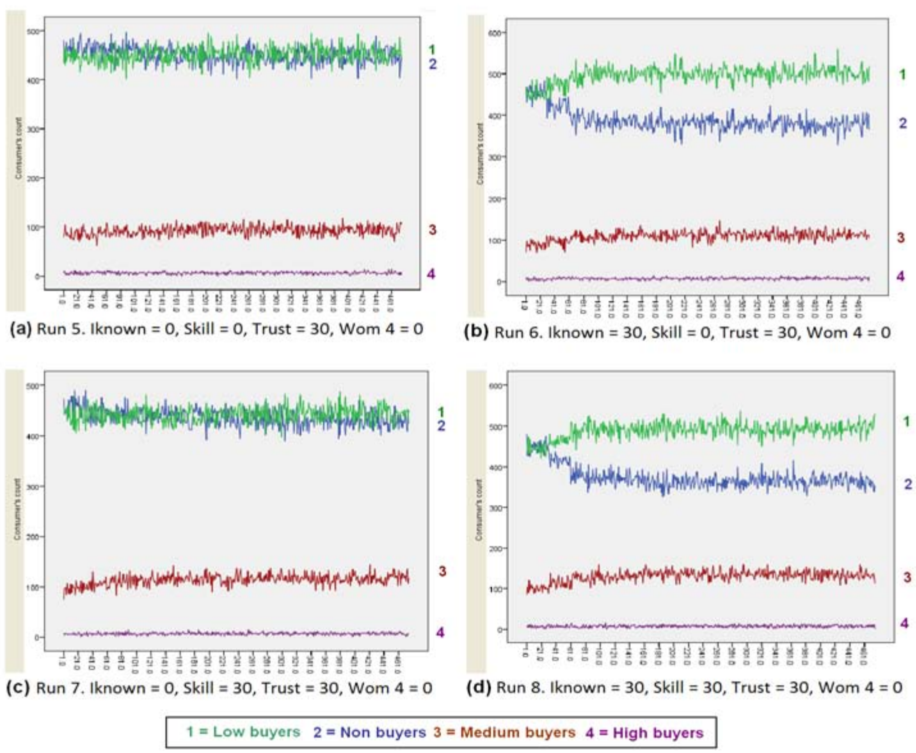


Figure 6–3: Runs 5 to 8. 2^4 factorial design

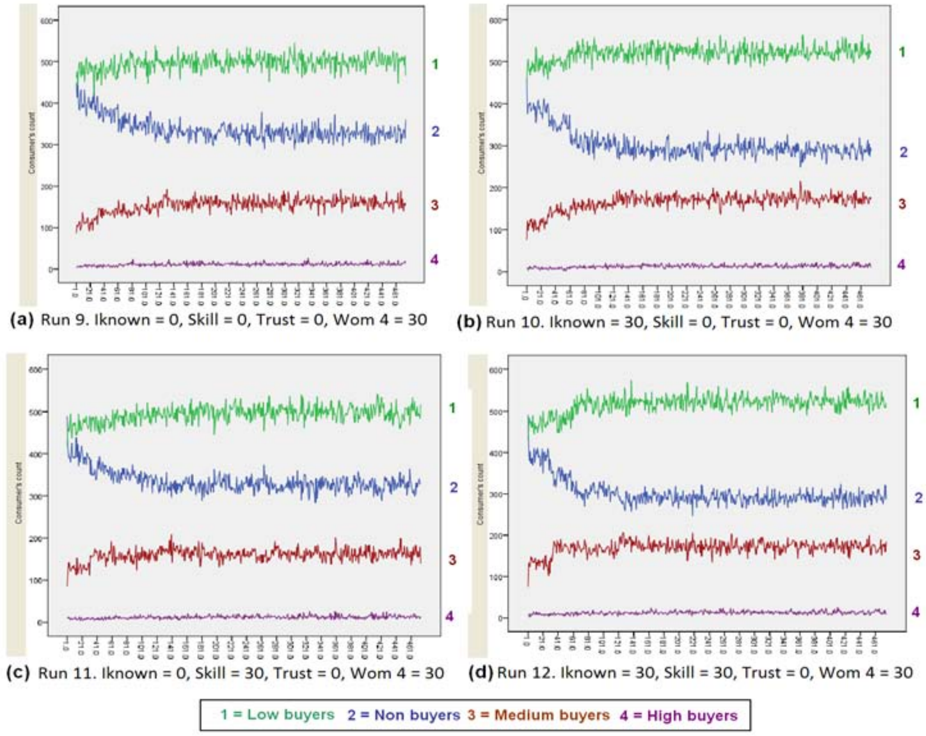


Figure 6–4: Runs 9 to 12. 2^4 factorial design

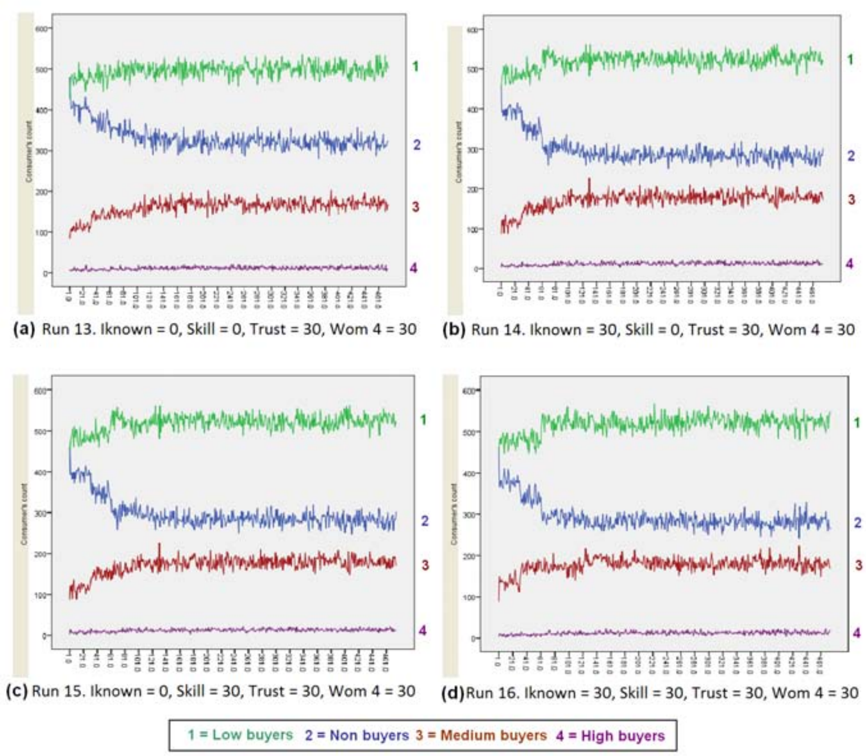


Figure 6–5: Runs 13 to 16. 2^4 factorial design

the number of non buyers. The graph shows an almost imperceptible difference in the proportions of each categories of buyers (Figure 6–2 (a) and (c)).

Runs five to eight show the result when there is an increment in the level of variable “Trust”, that is, keeping this variable in high level (Figure 6–3). It can be seen from the graph (Figure 6–3 (b) and (d)) that a greater decrement in the number of non buyers is achieved when an increment in the consumers’ “Trust” variable (security perception during the online transaction process) goes along with an increment in the level of knowledge in online transactions. There is a slight decrement in the number of non buyers when a high level of “Trust” is used alone or when applied along with a high level of “Skill”((Figure 6–3 (a) and (c)).

Figures 6–4 and 6–5 shows the results of the simulation when applying high levels of “Wom4” (run 9 to run 16). We can also notice a huge difference in the proportions of the categories of consumers when comparing with the results when this variable was mantained at its low level (Figure 6–2 and Figure 6–3). In addition, we also note the contributions of this variable used along with the variable ‘Iknown” (Figure 6–4 (d)) which achieves a very significant reduction in the number of non-buyers in addition to the increment in the number of low and medium buyers.

This mapping allowed us to have an overview of the impact and contributions of the four factors identified for the experiment. The next section formalizes this analysis and confirms our findings by performing an Analysis of Variance (ANOVA).

6.2 Analysis of Variance

We performed the Analysis of Variance (ANOVA) in order to confirm the magnitude of the effects of the four variables in the decrement in the rate of non-buyers. We also use the analysis of variance to formally test for significance of main effects and interaction between factors.

Prior to this analysis the data had to be truncated in order to analyze the system in its steady state. In Figure 6–2 we note that there are two clearly defined periods.

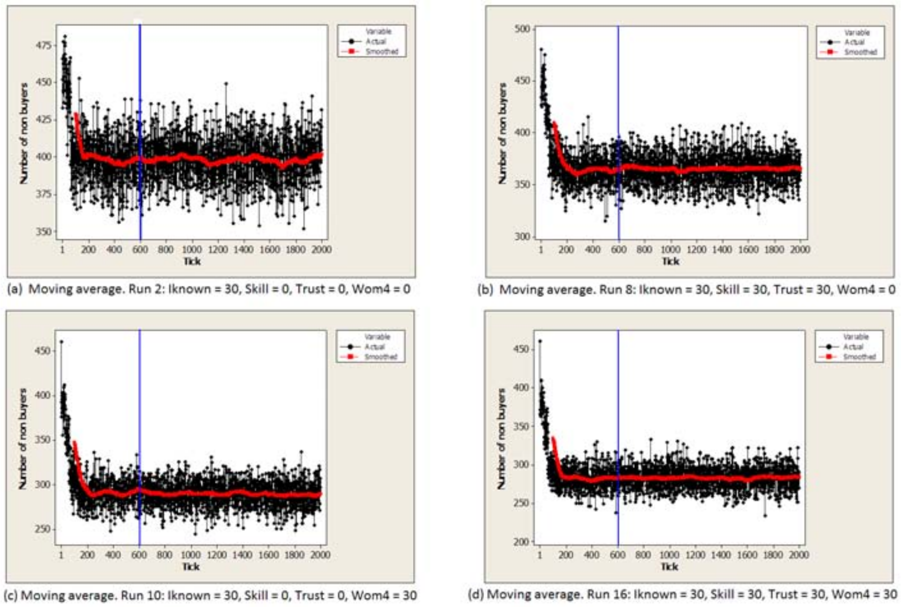
The first one shows the decrement in the rate of non buyers and the increment in the number of low and medium buyers when the factor values are increasing. The second period shows a state of stability for each of the sixteen runs. This event is generated when the values of the factors used in the experiment has reached its maximum value and therefore there is no further increment in their values. Hence the rate of each of the categories of buyers are going to remain stable. Furthermore, since this simulation is considered as a non terminal system, i.e it does not have a natural condition of completion, the corrective actions must be taken before analyzing the results.

For this purpose, it was necessary to eliminate the transition period to avoid any observation contained in the transition phase that bias the results. Moreover, is in the steady state where any measure of performance is stabilized.

We used the "Moving Average" technique with a parameter k = 100 to visually observe the period of time at which the measure of performance, in this case the number of non buyers, begins to present stablility which marks the end of the period of transition.

Figure 6–6 shows an example resulting from applying the "moving average" technique to the dependent variable of the experiment (number of non buyers). Figure shows the results for runs 2, 8, 10 and 16, where we noted that the transition period ends around observation 600, which is the point where the runs were truncated.

The analysis of variance, assume that variances are equal across groups or samples. In this case we used the Levene test of equality of equal variances [68] in order to verify that assumption. Table 6–1 shows the results from applying the Leneve test. The null hypothesis is defined as the variance of the error term is constant across the cells defined by the combination of factor levels. Since the



(a) Moving average. Run 2: Iknown = 30, Skill = 0, Trust = 0, Wom4 = 0

(b) Moving average. Run 8: Iknown = 30, Skill = 30, Trust = 30, Wom4 = 0

(c) Moving average. Run 10: Iknown = 30, Skill = 0, Trust = 0, Wom4 = 30

(d) Moving average. Run 16: Iknown = 30, Skill = 30, Trust = 30, Wom4 = 30

Figure 6–6: Moving average for non buyers. k = 100

significance value of the test, 0.286, is greater than 0.05, there is no reason to believe that the equal variances assumption is violated.

Table 6–1: Levene's Test of Equality of Error Variances

Dependent Variable:NonBuyer			
F	df1	df2	Sig.
1.172	15	15984	0.286

From Table 6–2, we note that the main effects of each variable "Wom4", "Iknown", "Skill"' and "Trust" are statistically significant (the significant value for each factor is less than 0.05). There is also interaction between variables that appears to be statistically significant. The R^2 and the adjusted R^2 statistic indicate that the full model would be expected to explain about 94.8% of the variability in new data.

Table 6–2: Analysis of Variance for the proportion of non buyers

Dependent Variable:NonBuyer								
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed $Power^b$
Corrected Model	6.225E7	15	4.149E6	1.940E4	.000	.948	2.910E5	1.000
Intercept	2.070E9	1	2.070E9	9.678E6	.000	.998	9.678E6	1.000
Iknown	1.070E7	1	1.070E7	5.003E4	.000	.758	5.003E4	1.000
Skill	2.145E5	1	2.145E5	1002.848	.000	.059	1002.848	1.000
Trust	6.738E5	1	6.738E5	3149.586	.000	.165	3149.586	1.000
Wom4	4.926E7	1	4.926E7	2.303E5	.000	.935	2.303E5	1.000
Iknown * Skill	207.708	1	207.708	.971	.324	.000	.971	.166
Iknown * Trust	883.130	1	883.130	4.128	.042	.000	4.128	.529
Iknown * Wom4	1.046E6	1	1.046E6	4891.941	.000	.234	4891.941	1.000
Skill * Trust	148.418	1	148.418	.694	.405	.000	.694	.132
Skill * Wom4	18.411E4	1	1.841E5	860.662	.000	.051	860.662	1.000
Trust * Wom4	16.370E4	1	1.637E5	765.273	.000	.046	765.273	1.000
Iknown * Skill * Trust	4.323	1	4.323	.020	.887	.000	.020	.052
Iknown * Skill * Wom4	320.073	1	320.073	1.496	.221	.000	1.496	.231
Iknown * Trust * Wom4	192.063	1	192.063	.898	.343	.000	.898	.157
Skill * Trust * Wom4	441.228	1	441.228	2.063	.151	.000	2.063	.301
Iknown * Skill * Trust * Wom4	63.883	1	63.883	.299	.585	.000	.299	.085
Error	3.419E6	15984	213.918					
Total	2.136E9	16000						
Corrected Total	6.566E7	15999						
a. R Squared = .948 (Adjusted R Squared = .948)								
b. Computed using alpha = .05								

The significant main effects tell us that there are significant differences when the values of all factors were incremented over time to reach their highest level. This means the decrement in the number of non-buyers.

The factor having the more contribution in reducing the number of non buyers resulted the variable “Wom4”, which means that when consumers start to feel confidence in the reviews presented in the web site, it was obtained the largest drop in the number of non buyers. Next in importance are the variables “Iknown”, “Trust” and finally “Skill”.

From the above analysis it can be argued that the knowledge acquired by the consumer about how online transactions operates and the web site security mechanisms (“Iknown”) are crucial in reducing the number of non buyers for the population studied, as well as the perceived security on the website ("Trust") and skills that the consumer has when doing online purchases ("Skill").

On the other hand, we can also analyse the interactions resulting significant. Figure 6–4 plots the response data, where we can observe interactions between factors. In this case we are interested in three interaction resulting significant in the model: "IKnown" * "Wom4", "Skill" * "Wom4" and "Trust" * "Wom4".

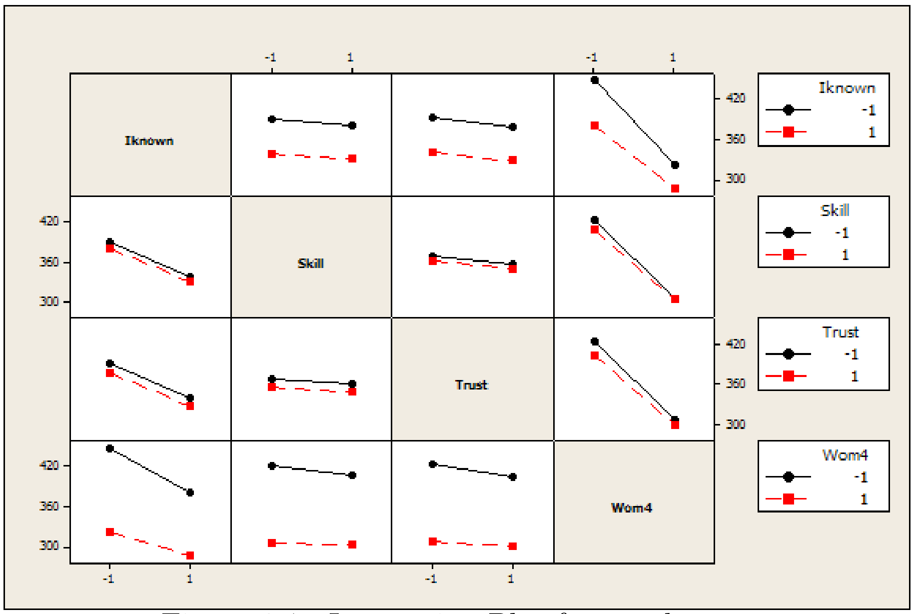


Figure 6–7: Interaction Plot for non buyers

Note from row four of the interaction matrix in Figure 6–7 that when low levels of "Wom4" are applied, i.e when there is only an increment in the value of the remaining variables, there is a decrement in the number of non buyers, given the individual contribution of variables "IKnown", "Skill" and "Trust". However, when combined with high levels of "Wom4" the decrement is much more coming to greatly reduce the number of non buyers.

Looking at column four in Figure 6–7, we can note that for high levels of "Wom4", increasing the consumers' knowledge in online transactions is achieved to further reduce the number of non buyers (row 1 column 4 of the matrix). This does not apply when there is an increment in the value of variable "Skill", as shown in row 2 column 4 of the matrix, in which the effect of this increment does not affect the decrement in the number of non buyers. Finally, for high level of “Wom4”, an increment in variable “Trust” provides little increment in the declining number of non buyers.

6.3 Estimated marginal means

Table 6–3 displays the estimated marginal means and standard errors of the numbers of non buyers at each factor level combinations of “Iknown”, “Skill”, “Trust” and “Wom4”. These means are predicted means, not observed, and are based on the specified model for this experiment. The results are presented in ascending order begining with the combination of factors that achieved the best reduction in the number of non buyers and finishing in the combination represented by the lack of increment in the level of each factor resulting in the greater number of non buyers. Number 1 represents a one point increment in the represented factor for every 30 “ticks” in each the simulation run, while number -1 represent no increment.

Table 6–3: Estimated marginal means

Dependent Variable: number of non buyers							95% Confidence Interval	
Run	Iknown	Skill	Trust	Wom4	Mean	Std. Error	Lower Bound	Upper Bound
16	1	1	1	1	283.094	0.4623	282.187	284.000
14	1	-1	1	1	283.921	0.4623	283.014	284.827
12	1	1	-1	1	289.219	0.4623	288.312	290.125
10	1	-1	-1	1	289.580	0.4623	288.673	290.486
15	-1	1	1	1	318.107	0.4623	317.200	319.013
13	-1	-1	1	1	318.637	0.4623	317.730	319.543
11	-1	1	-1	1	325.423	0.4623	324.516	326.329
9	-1	-1	-1	1	325.861	0.4623	324.954	326.767
8	1	1	1	-1	365.230	0.4623	364.323	366.136
6	1	-1	1	-1	378.143	0.4623	377.236	379.049
4	1	1	-1	-1	383.671	0.4623	382.764	384.577
2	1	-1	-1	-1	397.952	0.4623	397.045	398.858
7	-1	1	1	-1	432.212	0.4623	431.305	433.118
5	-1	-1	1	-1	446.465	0.4623	445.558	447.371
3	-1	1	-1	-1	451.473	0.4623	450.566	452.379
1	-1	-1	-1	-1	466.457	0.4623	465.550	467.363

We can observe again that for expecting to achieve further reduction in the number of non buyers, all factors have to be in their high level. However, when we compare 16 and 14 there only exists a little difference in the reduction of the number of non buyers (283.094 and 283.921). This is because variable "Skill" has very little contribution in the dependent variable.

Furthermore, we expect to reduce the number of non buyers with an increment in the value of the variables having the greatest contribution in this case "Wom4" and " Iknown". Comparing the expected values from runs 1 and 10 we expect a great reduction in the number of non buyer from 466.457 to 289.580 when both variables ("Wom4" and " Iknown") are in their high levels.

On the other site, interpretating the simulation "ticks" from a practical view, i.e. each "tick" representing a time period, one could say that each "tick" represents a day (in the best case where there is a great activity in e-commerce since every consumer is likely to buy a product daily). The total simulation time (2000 ticks) represents in this case five years and four months aproximately. During this time, it was found that the data began to stabilize when the simulation runs approximately 600 ticks. With the previous consideration we can say that stability is achieved after about a year and seven months of simulation run.

On a worst case, when each "tick" represents a week, the simulation time consists in about 36 years and the stability is achieved after aproximately 10 years and 2 months.

In next chapter we expose the principal conclusions based on the experiment and results discussed above. We also presents suggestions for future investigations we thought would be interesting to continue.

CHAPTER 7
CONCLUSION AND FUTURE WORK

In this thesis work we wanted to perform the analysis of a complex system in which its components, in this case online consumers, have a particular behavior represented by its intrinsic and extrinsic characteristics that generate a collective behavior due to the interaction with other components .

The first stage of this thesis has shown that the resulting seven factors from the empirical study are consistent with previous studies [4, 5, 10, 13 and 14] and also adjusted very well to the variables defined in the conceptual model. The level of reliability obtained in each of the constructs (from 0.726 to 0.910) also demonstrates the strength of the measuring instrument developed. Hence, the seven factors identified are a significant contribution for future research in which one wants to determine the degree to which each of these factors affect the behavior of online consumers in the population studied.

Therefore, the seven dimensional components resulting from factor analysis and along with socio-demographic variables became the predictors for consumer behavior variables for the population represented by this sample. In this case, the target variables were defined as the number of times and the amount of money spent by consumers in the past six months as defined in the conceptual model.

With data collected from this particular population, it was possible to determine the best predictors for the two dependant variables defined. For the two target variables, the best predictor was the variable that has to do with the degree of confidence in the reviews presented on the website. Previous studies have shown that the design, usability and ratings displayed on the website influence customer purchase decision ([20] and [14]).

Also we were able to demostrate that the knowledge about how online transactions works (Iknown), the experience in the use of internet (Skill) [47] and the security perceptions in online transactions (Trust) [35], have been decisive for classifying likely versus unlikely consumer who buys online. However, other characteristics like gender or intrinsic characteristics such as disposition to trust, impulsive behavior and self efficacy do not appear as being influential in consumer's purchase decision for this population.

Given the disadvantage of CHAID to work with small samples ([55] and [56]), the misclassification risk seems to be a bit high. Using a larger sample could minimize this problem. However, using an agent-based modeling it was possible to represent a segment of the population that was little explored but definitively very important because of its characters to live in an era when most of their activities is conducted online.

The inclusion of decision rules derived from the classification trees in the multi-agent based simulation has created a solid model, given the need to represent the population segment studied.

Despite the simplicity and limitations of the research model, the interaction of the agents can produce complex emergent structures and dynamical behaviors of individuals and groups because the non-linear dynamic aspect of the agent's behavior and interactions. These emergent phenomena can not be explained by the micro-level units alone. The interactions of the units lead to a nonlinear transformation to macro-level phenomena. Our interest was in studying this complexity by discovering the basic underlying rules that describe most of the phenomena and how the classification tree analysis with CHAID has been useful in determining the rules of decision for each consumer group.

The analysis of the 2^4 factorial design, confirms that the variable that solidly contributes to reduce the rate of non-buyers isthe variable “Wom4”. According to the definition of this variable (Table 3–9) the degree of confidence in the reviews presented on the website is essential in the reduction of the number of non buyers. Also along with an increment in the consumers’ knowlegde about the procedures and security mechanism of online transactions (“Iknown”), an increment in the security perception in online transactions (“Trust”), and an increment in the habilities of using the Internet (“Skill”) generates a reduction in the proportion of non buyers.

This result also reflects the findings of Li and Zhang model [17] that conclude that the number of online purchases and the frequency consumers buy online is dependent to certain degree on their channel knowledge and perception of channel utilities. Moreover, their conceptual model (Figure 2–2), shows that a consumer with more knowledge of the Web site is more likely to have a positive perception of the channel utilities, which, in turn, will have a positive impact on actual online purchases.

Future work could be oriented to investigate other dimensions in consumer behavior that could be added to the model, for example other behavioral rules to represent how a consumer is likely to buy from a web site based on his own previous purchases experiences.

Furthermore, given the limitations of the model, future research may focus on include different attributes in the “Website_Agent” that represent the fact of buying on a website based on the contents and products offered. Another issue to include is the representation of the mistrust generated due negative reviews presented on the website or by the interaction with other consumer that could generate an adverse behavior to online shopping.

The process of acquiring more knowledge in online transactions, the process to become more skilled in using the internet and the process to gain confidence in the website have been simulated as a linear behavior. It only was represented by an increment in input parameters. However, future work may include models of adaptation and learning to investigate emergence of strategies.

APPENDIXES

APPENDIX A
PILOT EXPERIMENT

The first iteration of factor analysis was performed by using all questions (except socio-demographic questions). Factor analysis for the pilot experiment created 7 components in which we can observed that more than one question fell in other construct different to the originalfounded in the literature.

Second iteration was done eliminating those questions that do not have a likert scale. The technology knowledge questions considered in the first iteration falls in this group.

Table A–1 lists the eigenvalues associated with each linear component (factor) before extraction, after extraction and after rotation. The eigenvalues associated with each factor, represent the variance explained by that particular linear component. The table also displays the eigenvalues in terms of percentage of variance explained.

Due to the fact that the determinant of the resultant correlation matrix has a value of zero, apparently there were problems of multicolinearity (items that measure the same thing). Items with an inter-item correlation value greater than 0.80 should be eliminated in order to solve this problem.

Three groups of questions were identified to have correlation coefficients greater than 0.80 and therefore we proceeded to eliminate one variable from each group. Hence, questions corresponding to variables ImpBhvior4, Trust3 and Trust5 were eliminated before continue with the factor analysis.

Table A–1: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**7.797**	21.658	**21.658**	7.797	21.658	**21.658**	4.903	13.620	13.620
2	**6.470**	17.974	**39.631**	6.470	17.974	**39.631**	4.401	12.225	25.845
3	**2.948**	8.189	**47.820**	2.948	8.189	**47.820**	3.852	10.699	36.544
4	**2.630**	7.304	**55.124**	2.630	7.304	**55.124**	3.244	9.012	45.556
5	**2.421**	6.724	**61.849**	2.421	6.724	**61.849**	2.817	7.824	53.380
6	**2.170**	6.027	**67.876**	2.170	6.027	**67.876**	2.751	7.643	61.023
7	**1.749**	4.859	**72.736**	1.749	4.859	**72.736**	2.564	7.122	68.145
8	**1.296**	3.601	76.337	1.296	3.601	76.337	2.425	6.735	74.880
9	**1.190**	3.305	79.642	1.190	3.305	79.642	1.714	4.762	79.642
10	.962	2.672	82.314						
11	.850	2.361	84.674						
12	.752	2.089	86.764						
13	.700	1.943	88.707						
14	.634	1.761	90.468						
15	.526	1.460	91.929						
16	.465	1.293	93.222						
17	.433	1.204	94.426						
18	.350	.972	95.398						
19	.320	.889	96.287						
20	.263	.731	97.018						
21	.182	.506	97.524						
22	.177	.492	98.016						
23	.143	.396	98.412						
24	.128	.355	98.767						
25	.106	.295	99.062						
26	.086	.239	99.301						
27	.069	.192	99.493						
28	.059	.164	99.657						
29	.054	.149	99.806						
30	.028	.079	99.885						
31	.020	.057	99.942						
32	.011	.030	99.972						
33	.007	.020	99.992						
34	.002	.005	99.997						
35	.001	.003	100.000						
36	2.420E-16	6.723E-16	100.000						

Table A–2: Multicolineared items

	ImpBhvior3	ImpBhvior4	ImpBhvior5	Trust 2	Trust 3	Trust 5	Trust 6
ImpBhvior3	1.000	**0.822**					
ImpBhvior4	**0.822**	1.000	**0.808**				
ImpBhvior5		**0.808**	1.000				
Trust 2				1.000	**0.811**		
Trust 3				**0.811**	1.000		
Trust 5						1.000	**0.805**
Trust 6						**0.805**	1.000

The resulted rotated factor matrix from the pilot experiment is shown in table A–3. We can see the seven components generated by Varimax rotation.

Table A–3: Rotated Component Matrix - 7 components

	Component						
	1	2	3	4	5	6	7
SelfEfficacy6	**.795**						
SelfEfficacy5	**.770**						
SelfEfficacy4	**.762**						
SelfEfficacy2	**.759**						
DispTrust5	**.634**				.417		
SelfEfficacy3	**.628**						
SelfEfficacy1	**.621**						
DispTrust3	**.594**			.425			
ImpBhvior6		**.792**					
ImpBhvior7		**.790**					
ImpBhvior3		**.735**					
ImpBhvior5		**.702**	.401				
ImpBhvior2		**.691**					
ImpBhvior1		**.628**					
PercepRisk3		**.611**					
ImpBhvior12			**.778**				
ImpBhvior11			**.758**				
ImpBhvior10			**.732**				
ImpBhvior8			**.644**				
ImpBhvior13			**.585**		.457		
DispTrust2				**.842**			
ImpBhvior9				**.829**			
DispTrust4	.402			**.670**			
DispTrust1	.416			**.659**			
PercepRisk4					**.876**		
PercepRisk5					**.869**		
Trust6					**-.401**		
Trust4						**.832**	
PercepRisk1						**749**	
PercepRisk2				.494		**.587**	
ImpBhvior14						**.567**	
Trust2							**.831**
Trust1							**.722**

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 9 iterations.

Cronbach's alpha was calculated for every construct obtained previously. The reliability coefficient results for the 7 components extracted are summarized in table A–4. The values of Cronbach's alpha range from 0.617 to 0.896, therefore they fall in the acceptable region.

Before having this final version of components extracted and their correspondent items, some considerations were taken. In some components there were questions needed to be eliminated in order to increase the value of alpha.

Table A–4: Reliability coefficient

Components	**Items**	**Factor loadings**	**Cronbach's alpha**
Component 1	DispTrust3	.594	.863
	DispTrust5	.634	
	SelfEfficacy1	.621	
	SelfEfficacy2	.759	
	SelfEfficacy3	.628	
	SelfEfficacy4	.762	
	SelfEfficacy5	.770	
	SelfEfficacy6	.795	
Component 2	ImpBhvior1	.628	.896
	ImpBhvior2	.691	
	ImpBhvior3	.735	
	ImpBhvior5	.702	
	ImpBhvior6	.792	
	ImpBhvior7	.790	
Component 3	ImpBhvior10	.732	.859
	ImpBhvior11	.758	
	ImpBhvior12	.778	
	ImpBhvior13	.585	
	ImpBhvior8	.644	
Component 4	DispTrust1	.659	.824
	DispTrust2	.842	
	DispTrust4	.670	
	ImpBhvior9	.829	
Component 5	PercepRisk4	.876	.812
	PercepRisk5	.869	
Component 6	ImpBhvior14	.567	.617
	PercepRisk1	.749	
	PercepRisk2	.587	
	Trust4	.832	
Component 7	Trust1	.722	.782
	Trust2	.831	

APPENDIX B
ONLINE QUESTIONNAIRE

Universidad de Puerto Rico en Mayagüez
Decanato de Asuntos Académicos
Comité para la Protección de los Seres Humanos en la Investigación

07-08 EG 02

4 de junio de 2008

Sr. Eleazar Gil Herrera
P.O. Box 5840
Mayagüez, P. R., 00681

Estimado Sr. Gil Herrera:

Su carta fechada el 21 de mayo ha atendido satisfactoriamente las interrogantes planteadas por el CPSHI. Me complace, pues, conceder la aprobación de su propuesta de investigación titulada ***A Multi-Agent Framework for Consumer Behavior and Purchase Intentions in Electronic Commerce.*** La aprobación se extiende desde el 5 de junio de 2008 hasta el 5 de junio de 2009. Cualquier modificación en la participación de los sujetos humanos en su estudio requeriría una nueva revisión por este Comité.

Le deseo éxito en su proyecto de investigación.

Atentamente,

Jorge J. Ferrer

Jorge J. Ferrer, Ph.D.
Presidente CPSHI
UPR en Mayagüez

Cc.
Dr. Agustín Rullán, Director del Departamento de Ingeniería Industrial
Dra. Viviana Cesaní, Presidenta del Comité Garduado

UPRM. Industrial Engineering Department

Thesis Questionnaire

-

Dear Participant:
My name is Eleazar Gil, a graduate student at University of Puerto Rico, Department of Industrial Engineering. I am carrying out a research under the supervision of PhD Viviana Cesaní, Associate Professor of the Department of Industrial Engineering.

The title of my thesis is:
"A MULTI –AGENT FRAMEWORK FOR CONSUMER BEHAVIOR AND PURCHASE INTENTIONS IN ELECTRONIC COMMERCE."

I am requesting you to participate in this study as a respondent to my questionnaire.

In this study, you will response several questions about what is your behavior when you choose the Internet as the medium to carry your purchases.

What you have to do is answer direct questions or answer different situations where you will response according to which resemble more to your opinion.

There is no correct or wrong answer, simply a personal opinion. You do not have to write your name or any form of identification. The information you provide will be strictly confidential and used only for the purpose of this research.

Your participation is voluntary, and you can refuse to answer these questions without any penalty or repercussion. This exercise will take, at most, 20 minutes. If you have any concern or question regarding this research, please do not hesitate to contact us. You can reach us using the following e-mail addresses: eleazar.gil@upr.edu or vcesani@uprm.edu

Thank you for your participation.
Sincerely,
Eleazar Gil,
MsC. Student
Department of Industrial Engineering.

I agree

UPRM. Industrial Engineering Department

Thesis Questionnaire
-

Please carefully read all the questions and then answer them with as much sincerity as possible. This information will be very useful to determine aspects of consumer behavior when making purchases online. Thank You.

Note: Required items are marked with *

SECTION 1: SOCIO-ECONOMIC CHARACTERISTICS Capture respondent's demographic characteristics as age, education level,income. Also captures experience purchasing online

1 * **Sex**	**Male** **Female**						
2 * **To which of the age groups do you belong?**	16-20	21-26	27-33	34-43	44-51	52-62	62 +
3 * **Are you currently a student?** if no, go to question number 5.	**No** **Yes**						
4 **Student status**	**Underdraduate** **Graduate**						
5 * **Work status**	**Partial** **Full time** **Not currently working** **Other**						
6 * **What is your education level?**	**High school graduate** **College graduate** **Master's degree** **Doctoral's degree** **Professional degree** **Other**						
7 * **What is your family's annual income level?**	**Under $25,000** **$25,000 - $ 50,000** **$50,000 - $75,000** **$75,000 - $100,000** **Over $100,000**						
8 * **Your budget for your own expenses per month is:**	**Less than $100** **$100 - $200** **$201- $300** **$301 - $500** **More than $500**						
9 * **How many times have you purchased product through the internet within the past six months?**	**None** **About 1 to 5 times** **About 6 to 10 times** **About 11 to 20 times** **About 21 to 40 times** **More than 40 times**						

10 * Aproximetly how much money did you spend on online shopping in the last six months?	◌ Nothing ◌ $1 to $200 ◌ $201 - $400 ◌ $401 - $600 ◌ $601 - $800 ◌ $801 - $1000 ◌ More than $1000
11 Select the items that you have purchased through the Internet in the last 6 months.	☐ Clothing ☐ Books ☐ Movie tickets ☐ Travel tickets ☐ Computer products ☐ Electronic products ☐ Cars ☐ Music ☐ Movies ☐ Other

SECTION 2: Disposition to trust Choose the alternative that most accurate with you

1 * I generally trust other people	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
2 * I tend to rely on other people.	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
3 * I generally have faith in humanity	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
4 * I feel that people are generally reliable	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
5 * I generally trust other people unless they give me reasons not to.	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree

SECTION 3: QUESTIONS ABOUT IMPULSIVE BEHAVIOR The following ten items indicate how well each of these points describes you:

1 * I often buy things spontaneously	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
2 * "Just do it" describes the way I buy things	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
3 * I often buy things without thinking.	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree

4 * **"Buy now, think about it later" describes me.**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
5 * **Sometimes I feel like buying things on the spur-of-the-moment.**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
6 * **I buy things according to how I feel at the moment.**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
7 * **Sometimes I am a bit reckless about what I buy**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
8 * **I avoid buying things that are not on my shopping list.**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree

SECTION 4: Technology Knowledge Capture the level of knowledge respondents have about internet, security in online transactions and online shopping procedures.	
1 * **How many hours per week do you spend on computer? (including spending on the web)**	**Below 5 hours** **from 5 to 10 hours** **from 10 -20 hours** **more than 20 hours**
2 * **Check the item if you have the ability to:**	☐ **1. Read and write e-mails, browsing news.** ☐ **2. Search for information over the internet.** ☐ **3. Share information posting in a web site (text, videos, photos, etc)** ☐ **4. Publish a web page**
3 * **Do you know how secure is your information (payment/ transaction information) when you realize purchases online?**	**No** **Yes**
4 * **Do you know what personal information does a web site gather?**	**No** **Yes**
5 * **Do you know if a web page shares the information it receives?**	**No** **Yes**
6 * **Do you know about services that enable businesses and people to make secure transactions over internet? (e.g Vesirign, TRUSTe, secure sockets layer)**	**No** **Yes**
7 * **Are you aware about identity fraud on internet? (e.g phishing).** In computing, phishing is an attempt to criminally and fraudulently acquire sensitive information, such as usernames, passwords and credit card details, by masquerading as a trustworthy entity in an electronic communication.	**No** **Yes**
8 * **Thinking how you use the internet and the sites you visit online, please select one of the following statements that most strongly reflects your use of the internet.** I use internet primarily for:	**Communication** **Entertaintment** **Research/information** **Shopping** **I use the internet equally for purposes of communication, entertaintment, research and shopping.**

	shopping.

SECTION 5: Security perceptions Capture the level of trust perception in online transactions.							
1 * **I am confident that the information I provide during any transactions will not reach inappropriate parties during storage in web retailer's databases.**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
2 * **I believe inappropriate parties cannot deliberately observe the information I provide during my transaction with a web retailer during transmission of data.**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree
3 * **In general, I do not trust the purchasing process in the web site as much as I trust traditional purchasing processes**	Strongly disagree	Mostly Disagree	Disagree somewhat	Neither agree nor disagree	Agree somewhat	Mostly agree	Strongly agree

Section 6: Perceptions of risk. Perceptions of risk regarding the web site that you have made a purchase.					
1 * **How much risk would you tolerate when deciding to make a purchase from the web sites?**	Absolutely no risk	Some risk	Medium risk	High risk	Significant risk
2 * **How would you rate your overall perception of risk from a web site?**	Absolutely no risk	Some risk	Medium risk	High risk	Significant risk

3 * **Purchasing from a web site would involve more product risk (i.e not working, defective product) when compared with more traditional ways of shopping**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
4 * **Purchasing from a web site would involve more financial risk (i.e fraud, hard to return) compared with more traditional ways of shopping**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree

Section 7: Online transaction self-efficacy Confidence when making a purchase in online vendor and influence by information in the web site.							
1 * **I am confident that I can obtain relevant information through online source (e.g., online discussion groups, reputation sites, etc) on the Web vendors whom I am planning to make online purchases**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree

purchases.				disagree			
2 * **I am confident that I am usually able to purchase exactly the item that I want from Web vendors.**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
3 * **I am confident that, in case my order does not come through in a satisfactory manner, I am able to take care of the problems of my own.**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
4 * **I am confident that I am able to find a trustworthy web vendor based on ratings (e.g. number of the start or the smiley faces) provided by other consumers.**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
5 * **I am confident that in case of merchandise I have purchased online turns out to be defective, I am able to return it without any problem.**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
6 * **I am confident that, if the web vendor I made an online purchase from would not take back a defective product, I am able to solve the problem through the assistant of a third party (e.g. friends, better business bureaus, or relevant govermental agencies**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree

Section 8. Source Expertise & Shopping Motivation							
1 * **I often influence other people in using the Internet for buying products or services.**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
2 * **Other people see me as a good source of information to make purchases on the Internet.**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
3 * **If I have the intention to buy a product on a website, my decision to purchase is based on the positive shopping experience of others (friends/relatives/user forums).**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
4 * **When I buy a product online, the reviews presented on the website make me confident in purchasing the product**	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree
5 * **I buy via Internet since I see that others make secure purchases by this medium**	Strongly	Mostly	Disagree	Neither agree	Agree Somewhat	Mostly	Strongly

secure purchases by this medium.	Strongly disagree	Mostly Disagree	Disagree Somewhat	Neither agree nor disagree	Agree Somewhat	Mostly agree	Strongly agree

Continue

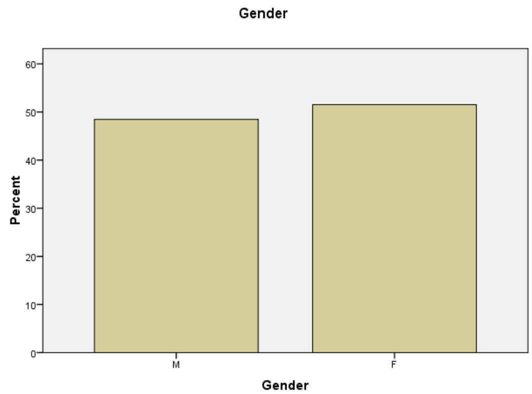
Cancel

APPENDIX C
EMPIRICAL DISTRIBUTION

Frequency Table

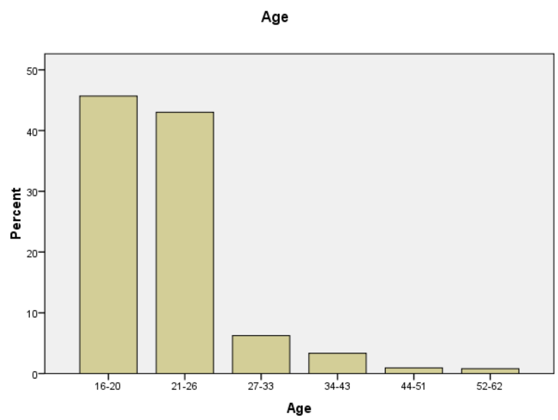
Gender

	Frequency	Percent	Valid Percent	Cumulative Percent
M	364	48.5	48.5	48.5
F	387	51.5	51.5	100.0
Total	751	100.0	100.0	



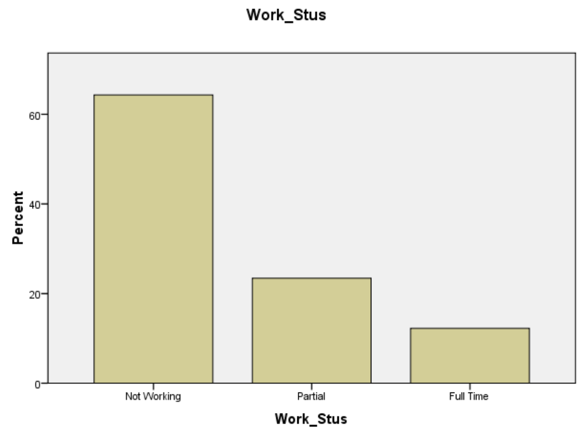
Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	16-20	343	45.7	45.7	45.7
	21-26	323	43.0	43.0	88.7
	27-33	47	6.3	6.3	94.9
	34-43	25	3.3	3.3	98.3
	44-51	7	.9	.9	99.2
	52-62	6	.8	.8	100.0
	Total	751	100.0	100.0	



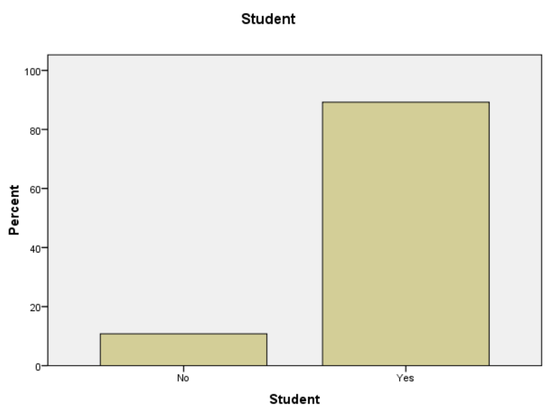
Work_Stus

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Working	483	64.3	64.3	64.3
	Partial	176	23.4	23.4	87.7
	Full Time	92	12.3	12.3	100.0
	Total	751	100.0	100.0	



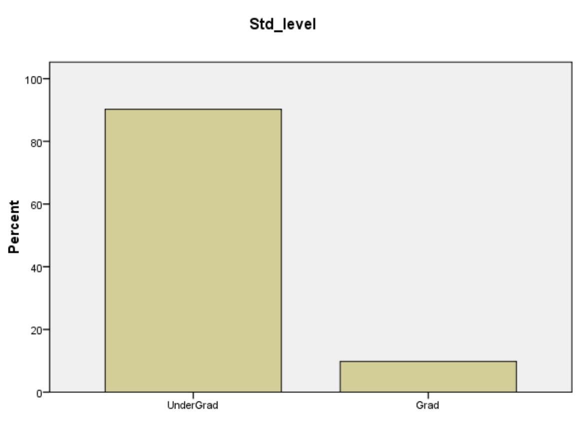
Student

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	81	10.8	10.8	10.8
	Yes	670	89.2	89.2	100.0
	Total	751	100.0	100.0	



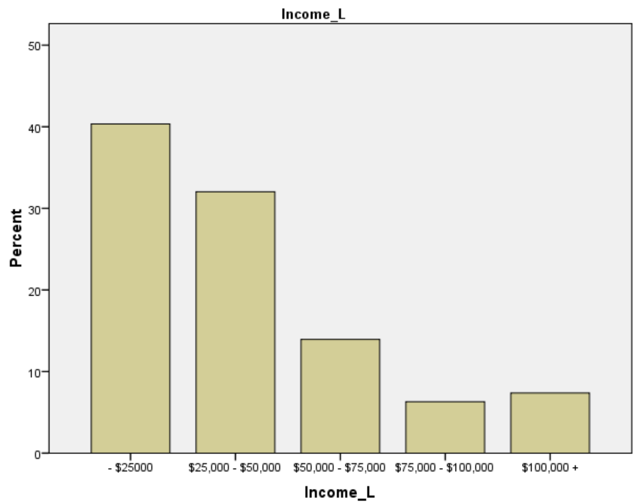
Std_level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	UnderGrad	627	83.5	90.2	90.2
	Grad	68	9.1	9.8	100.0
	Total	695	92.5	100.0	
Missing	System	56	7.5		
Total		751	100.0		



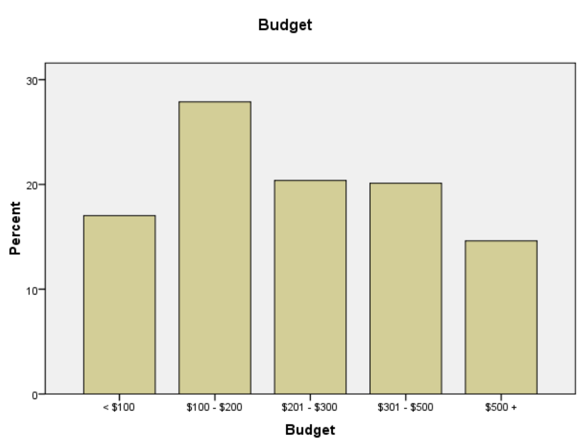
Income_L

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	- $25000	301	40.1	40.3	40.3
	$25,000 - $50,000	239	31.8	32.0	72.4
	$50,000 - $75,000	104	13.8	13.9	86.3
	$75,000 - $100,000	47	6.3	6.3	92.6
	$100,000 +	55	7.3	7.4	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



Budget

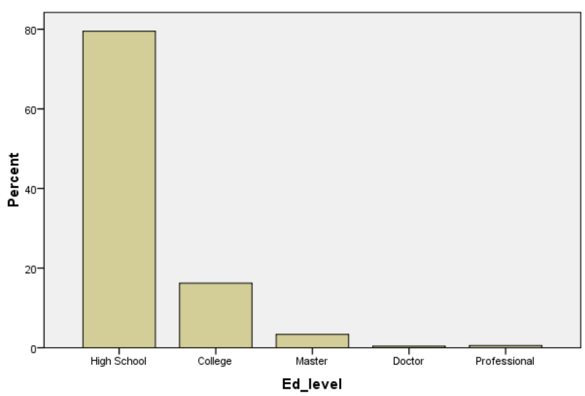
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	< $100	127	16.9	17.0	17.0
	$100 - $200	208	27.7	27.9	44.9
	$201 - $300	152	20.2	20.4	65.3
	$301 - $500	150	20.0	20.1	85.4
	$500 +	109	14.5	14.6	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



Ed_level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High School	593	79.0	79.5	79.5
	College	121	16.1	16.2	95.7
	Master	25	3.3	3.4	99.1
	Doctor	3	.4	.4	99.5
	Professional	4	.5	.5	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

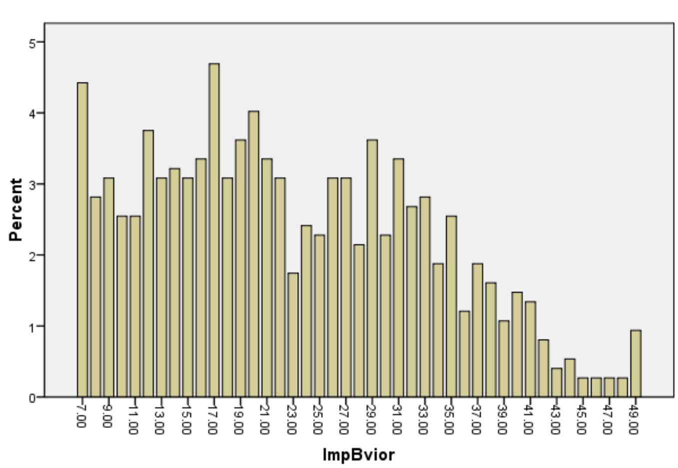
Ed_level



ImpBvior

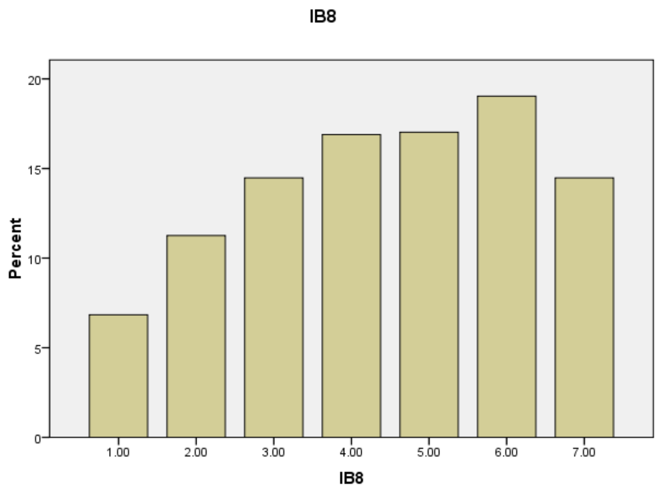
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	7	33	4.4	4.4	4.4
	8	21	2.8	2.8	7.2
	9	23	3.1	3.1	10.3
	10	19	2.5	2.5	12.9
	11	19	2.5	2.5	15.4
	12	28	3.7	3.8	19.2
	13	23	3.1	3.1	22.3
	14	24	3.2	3.2	25.5
	15	23	3.1	3.1	28.6
	16	25	3.3	3.4	31.9
	17	35	4.7	4.7	36.6
	18	23	3.1	3.1	39.7
	19	27	3.6	3.6	43.3
	20	30	4.0	4.0	47.3
	21	25	3.3	3.4	50.7
	22	23	3.1	3.1	53.8
	23	13	1.7	1.7	55.5
	24	18	2.4	2.4	57.9
	25	17	2.3	2.3	60.2
	26	23	3.1	3.1	63.3
	27	23	3.1	3.1	66.4
	28	16	2.1	2.1	68.5
	29	27	3.6	3.6	72.1
	30	17	2.3	2.3	74.4
	31	25	3.3	3.4	77.7
	32	20	2.7	2.7	80.4
	33	21	2.8	2.8	83.2
	34	14	1.9	1.9	85.1
	35	19	2.5	2.5	87.7
	36	9	1.2	1.2	88.9
	37	14	1.9	1.9	90.8
	38	12	1.6	1.6	92.4
	39	8	1.1	1.1	93.4
	40	11	1.5	1.5	94.9
	41	10	1.3	1.3	96.2
	42	6	.8	.8	97.1
	43	3	.4	.4	97.5
	44	4	.5	.5	98.0
	45	2	.3	.3	98.3
	46	2	.3	.3	98.5
	47	2	.3	.3	98.8
	48	2	.3	.3	99.1
	49	7	.9	.9	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

ImpBvior



IB8

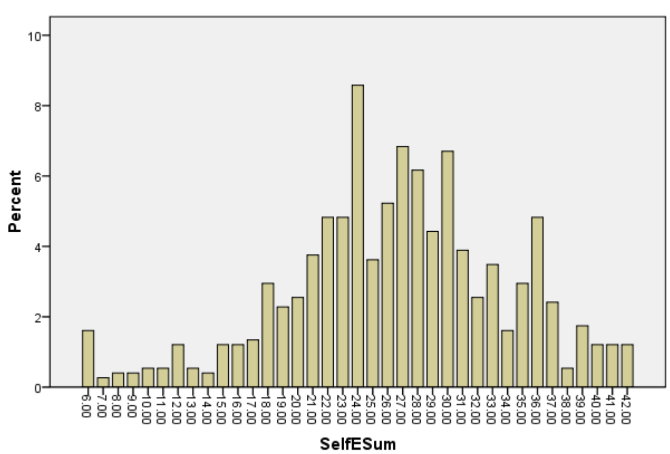
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	51	6.8	6.8	6.8
	2	84	11.2	11.3	18.1
	3	108	14.4	14.5	32.6
	4	126	16.8	16.9	49.5
	5	127	16.9	17.0	66.5
	6	142	18.9	19.0	85.5
	7	108	14.4	14.5	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



SelfESum

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	6	12	1.6	1.6	1.6
	7	2	.3	.3	1.9
	8	3	.4	.4	2.3
	9	3	.4	.4	2.7
	10	4	.5	.5	3.2
	11	4	.5	.5	3.8
	12	9	1.2	1.2	5.0
	13	4	.5	.5	5.5
	14	3	.4	.4	5.9
	15	9	1.2	1.2	7.1
	16	9	1.2	1.2	8.3
	17	10	1.3	1.3	9.7
	18	22	2.9	2.9	12.6
	19	17	2.3	2.3	14.9
	20	19	2.5	2.5	17.4
	21	28	3.7	3.8	21.2
	22	36	4.8	4.8	26.0
	23	36	4.8	4.8	30.8
	24	64	8.5	8.6	39.4
	25	27	3.6	3.6	43.0
	26	39	5.2	5.2	48.3
	27	51	6.8	6.8	55.1
	28	46	6.1	6.2	61.3
	29	33	4.4	4.4	65.7
	30	50	6.7	6.7	72.4
	31	29	3.9	3.9	76.3
	32	19	2.5	2.5	78.8
	33	26	3.5	3.5	82.3
	34	12	1.6	1.6	83.9
	35	22	2.9	2.9	86.9
	36	36	4.8	4.8	91.7
	37	18	2.4	2.4	94.1
	38	4	.5	.5	94.6
	39	13	1.7	1.7	96.4
	40	9	1.2	1.2	97.6
	41	9	1.2	1.2	98.8
	42	9	1.2	1.2	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

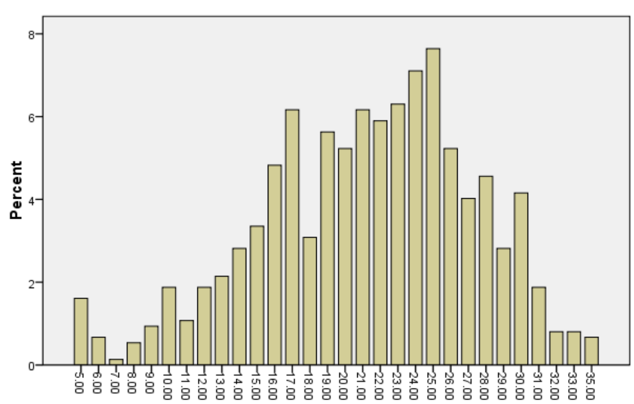
SelfESum



DispTrus

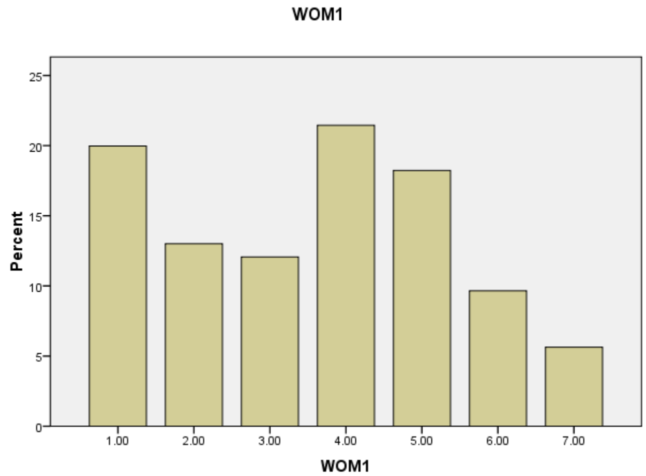
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	5	12	1.6	1.6	1.6
	6	5	.7	.7	2.3
	7	1	.1	.1	2.4
	8	4	.5	.5	2.9
	9	7	.9	.9	3.9
	10	14	1.9	1.9	5.8
	11	8	1.1	1.1	6.8
	12	14	1.9	1.9	8.7
	13	16	2.1	2.1	10.9
	14	21	2.8	2.8	13.7
	15	25	3.3	3.4	17.0
	16	36	4.8	4.8	21.8
	17	46	6.1	6.2	28.0
	18	23	3.1	3.1	31.1
	19	42	5.6	5.6	36.7
	20	39	5.2	5.2	42.0
	21	46	6.1	6.2	48.1
	22	44	5.9	5.9	54.0
	23	47	6.3	6.3	60.3
	24	53	7.1	7.1	67.4
	25	57	7.6	7.6	75.1
	26	39	5.2	5.2	80.3
	27	30	4.0	4.0	84.3
	28	34	4.5	4.6	88.9
	29	21	2.8	2.8	91.7
	30	31	4.1	4.2	95.8
	31	14	1.9	1.9	97.7
	32	6	.8	.8	98.5
	33	6	.8	.8	99.3
	35	5	.7	.7	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

DispTrus



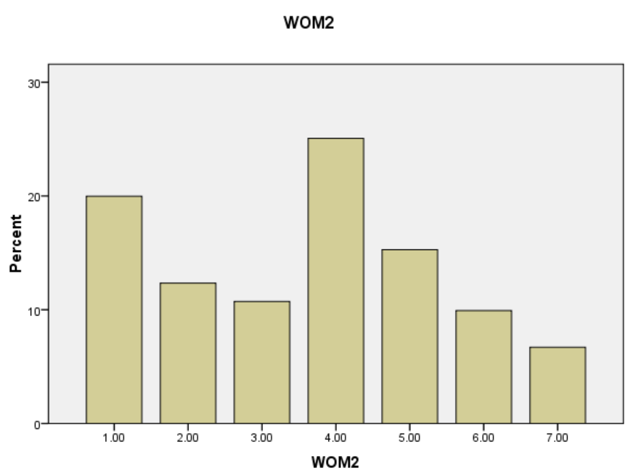
WOM1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	149	19.8	20.0	20.0
	2	97	12.9	13.0	33.0
	3	90	12.0	12.1	45.0
	4	160	21.3	21.4	66.5
	5	136	18.1	18.2	84.7
	6	72	9.6	9.7	94.4
	7	42	5.6	5.6	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



Wom2

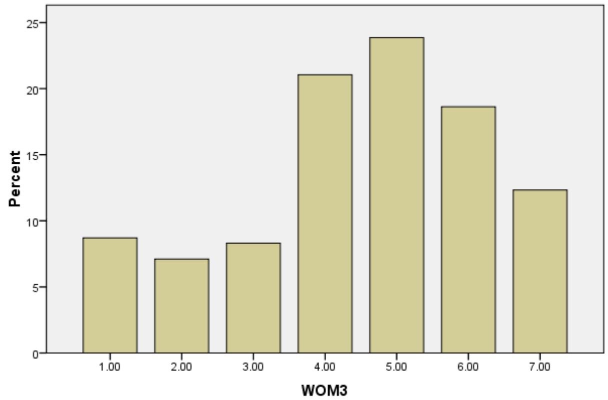
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	149	19.8	20.0	20.0
	2	92	12.3	12.3	32.3
	3	80	10.7	10.7	43.0
	4	187	24.9	25.1	68.1
	5	114	15.2	15.3	83.4
	6	74	9.9	9.9	93.3
	7	50	6.7	6.7	100.0
	Total	746.0	99.3	100.0	
	System	5.0	.7		
	Total	751.0	100.0		



WOM3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	65	8.7	8.7	8.7
	2	53	7.1	7.1	15.8
	3	62	8.3	8.3	24.1
	4	157	20.9	21.0	45.2
	5	178	23.7	23.9	69.0
	6	139	18.5	18.6	87.7
	7	92	12.3	12.3	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

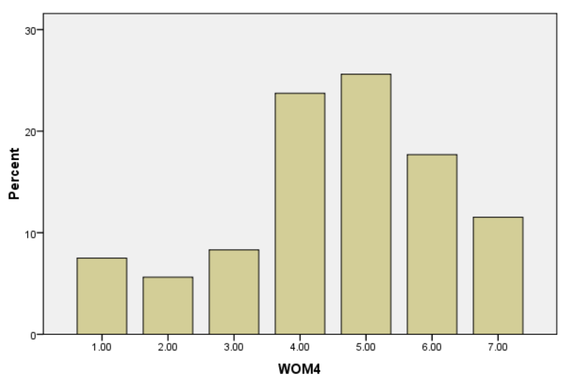
WOM3



WOM4

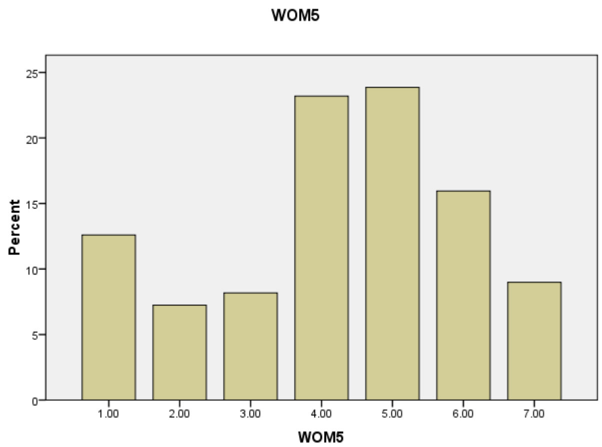
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	56	7.5	7.5	7.5
	2	42	5.6	5.6	13.1
	3	62	8.3	8.3	21.4
	4	177	23.6	23.7	45.2
	5	191	25.4	25.6	70.8
	6	132	17.6	17.7	88.5
	7	86	11.5	11.5	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

WOM4



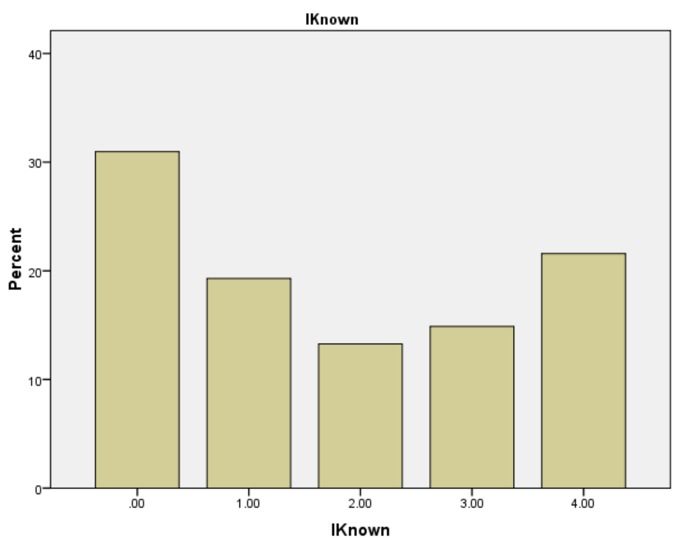
WOM5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	94	12.5	12.6	12.6
	2	54	7.2	7.2	19.8
	3	61	8.1	8.2	28.0
	4	173	23.0	23.2	51.2
	5	178	23.7	23.9	75.1
	6	119	15.8	16.0	91.0
	7	67	8.9	9.0	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



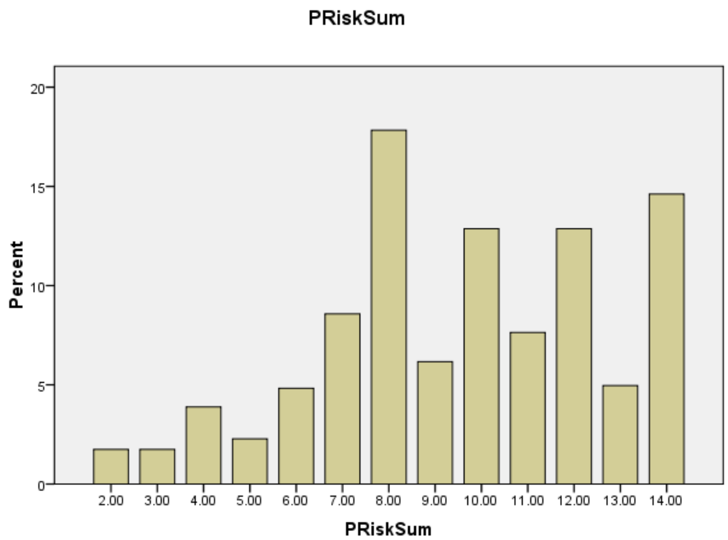
IKnownS

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	231	30.8	31.0	31.0
	1	144	19.2	19.3	50.3
	2	99	13.2	13.3	63.5
	3	111	14.8	14.9	78.4
	4	161	21.4	21.6	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



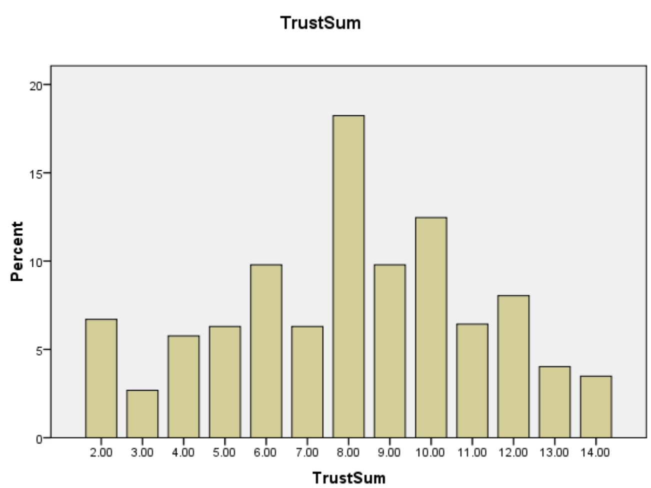
PRiskSum

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	13	1.7	1.7	1.7
	3	13	1.7	1.7	3.5
	4	29	3.9	3.9	7.4
	5	17	2.3	2.3	9.7
	6	36	4.8	4.8	14.5
	7	64	8.5	8.6	23.1
	8	133	17.7	17.8	40.9
	9	46	6.1	6.2	47.1
	10	96	12.8	12.9	59.9
	11	57	7.6	7.6	67.6
	12	96	12.8	12.9	80.4
	13	37	4.9	5.0	85.4
	14	109	14.5	14.6	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



TrustSum

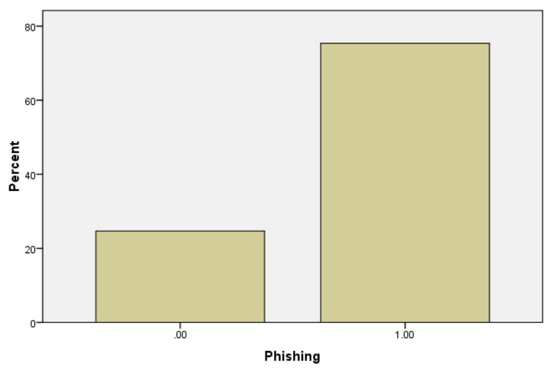
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	50	6.7	6.7	6.7
	3	20	2.7	2.7	9.4
	4	43	5.7	5.8	15.1
	5	47	6.3	6.3	21.4
	6	73	9.7	9.8	31.2
	7	47	6.3	6.3	37.5
	8	136	18.1	18.2	55.8
	9	73	9.7	9.8	65.5
	10	93	12.4	12.5	78.0
	11	48	6.4	6.4	84.5
	12	60	8.0	8.0	92.5
	13	30	4.0	4.0	96.5
	14	26	3.5	3.5	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		



Phishing

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	184	24.5	24.7	24.7
	1	562	74.8	75.3	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

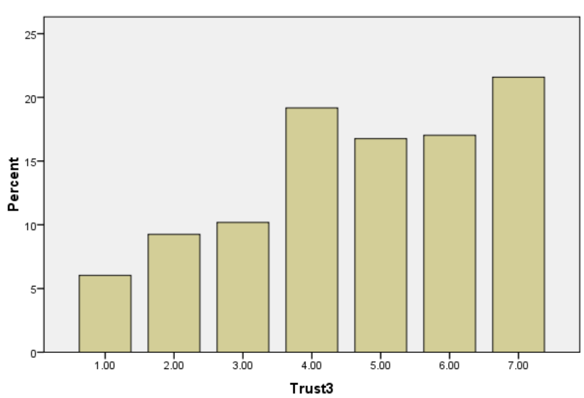
Phishing



Trust3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	45	6.0	6.0	6.0
	2	69	9.2	9.2	15.3
	3	76	10.1	10.2	25.5
	4	143	19.0	19.2	44.6
	5	125	16.6	16.8	61.4
	6	127	16.9	17.0	78.4
	7	161	21.4	21.6	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

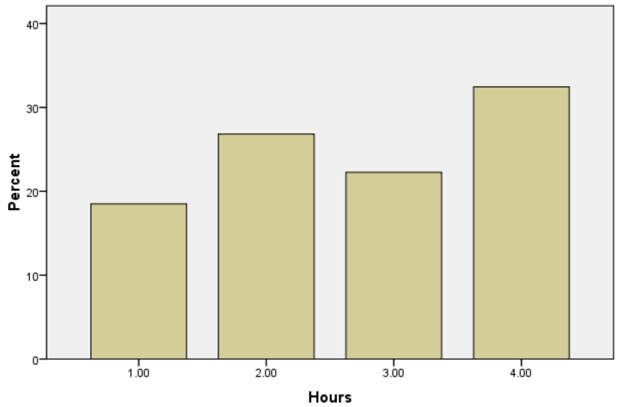
Trust3



Hours

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	138	18.4	18.5	18.5
	2	200	26.6	26.8	45.3
	3	166	22.1	22.3	67.6
	4	242	32.2	32.4	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

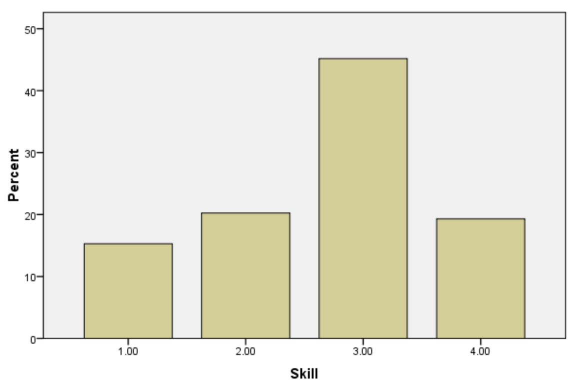
Hours



Skill

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	114	15.2	15.3	15.3
	2	151	20.1	20.2	35.5
	3	337	44.9	45.2	80.7
	4	144	19.2	19.3	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

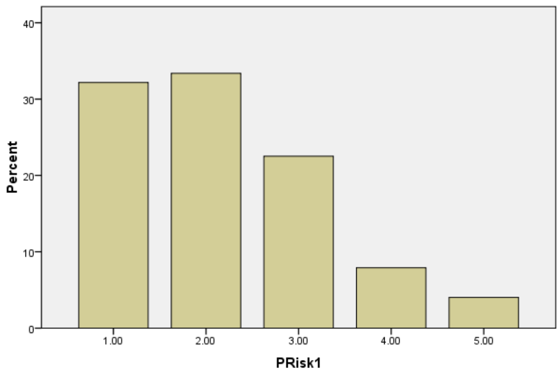
Skill



PRisk1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	240	32.0	32.2	32.2
	2	249	33.2	33.4	65.5
	3	168	22.4	22.5	88.1
	4	59	7.9	7.9	96.0
	5	30	4.0	4.0	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

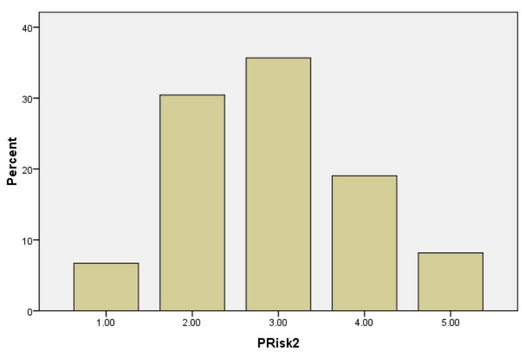
PRisk1



PRisk2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	50	6.7	6.7	6.7
	2	227	30.2	30.4	37.1
	3	266	35.4	35.7	72.8
	4	142	18.9	19.0	91.8
	5	61	8.1	8.2	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

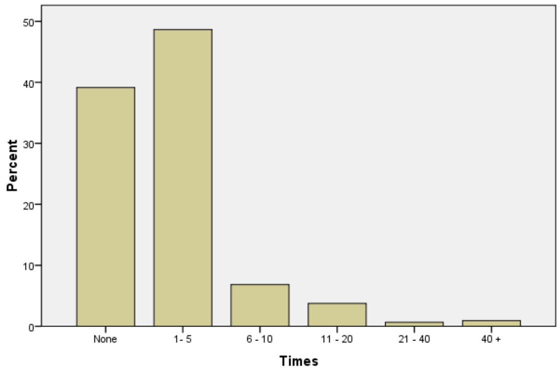
PRisk2



Times

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	292	38.9	39.1	39.1
	1- 5	363	48.3	48.7	87.8
	6 - 10	51	6.8	6.8	94.6
	11 - 20	28	3.7	3.8	98.4
	21 - 40	5	.7	.7	99.1
	40 +	7	.9	.9	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

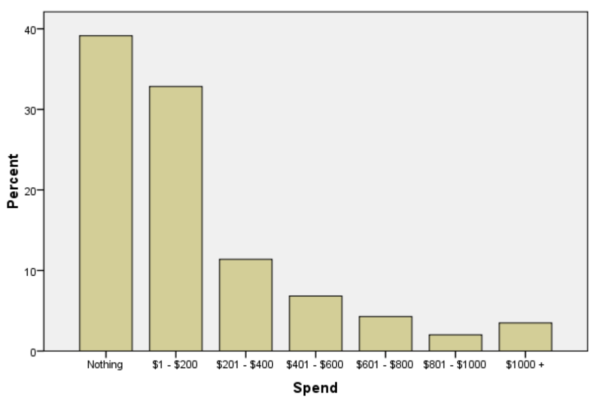
Times



Spend

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Nothing	292	38.9	39.1	39.1
	$1 - $200	245	32.6	32.8	72.0
	$201 - $400	85	11.3	11.4	83.4
	$401 - $600	51	6.8	6.8	90.2
	$601 - $800	32	4.3	4.3	94.5
	$801 - $1000	15	2.0	2.0	96.5
	$1000 +	26	3.5	3.5	100.0
	Total	746	99.3	100.0	
Missing	System	5	.7		
Total		751	100.0		

Spend



APPENDIX D
AGENT CLASSES IMPLEMENTED IN REPAST

```java
package abmproject;

import repast.simphony.context.Context;
import abmproject.WebSite;
import repast.simphony.engine.environment.RunEnvironment;
import repast.simphony.engine.schedule.ScheduledMethod;
import repast.simphony.parameter.Parameters;
import repast.simphony.space.continuous.ContinuousSpace;
import repast.simphony.space.continuous.NdPoint;
import repast.simphony.space.grid.Grid;
import repast.simphony.space.grid.GridPoint;
import repast.simphony.util.ContextUtils;

public class Consumer extends SimpleAgent {
	private String Gender;
	private double age;
	private String Work_Stus;
	private String Student;
	private String Ed_level;
	private int Famincome;
	private double Budget;
	private int Hours;
	private double Skill;
	private int phising;
	private int PRisk1;
	private int PRisk2;
	private int DispTrust;
	private int ImpBvior;
	private int Imp8;
	private double Trust3;
	private int SelfE;
	private double Trust;
	private int PRisk;
	private int WOM1;
	private int WOM2;
	private double WOM3;
	private double WOM4;
	private double WOM5;
	private double IKnown;
	private int Times;
	private int Spend;
	private String TimeScal;
	private String SpendSca;
	private  double noneBuyerLikelihood;
	private  double lowBuyerLikelihood;
	private  double medBuyerLikelihood;
	private  double highBuyerLikelihood;


	public double getNoneBuyerLikelihood() {
		return noneBuyerLikelihood;
	}
	public void setNoneBuyerLikelihood(double noneBuyerLikelihood) {
		this.noneBuyerLikelihood = noneBuyerLikelihood;
	}
	public double getLowBuyerLikelihood() {
		return lowBuyerLikelihood;
```

```
}
public void setLowBuyerLikelihood(double lowBuyerLikelihood) {
      this.lowBuyerLikelihood = lowBuyerLikelihood;
}
public double getMedBuyerLikelihood() {
      return medBuyerLikelihood;
}
public void setMedBuyerLikelihood(double medBuyerLikelihood) {
      this.medBuyerLikelihood = medBuyerLikelihood;
}
public double getHighBuyerLikelihood() {
      return highBuyerLikelihood;
}
public void setHighBuyerLikelihood(double highBuyerLikelihood) {
      this.highBuyerLikelihood = highBuyerLikelihood;
}


public Consumer( ) {  //constructor
      //this.setTimes(10);
      this.setHeading(Math.random()*360);

}
public String getWork_Stus() {
      return Work_Stus;
}
public void setWork_Stus(String work_Stus) {
      Work_Stus = work_Stus;
}
public String getEd_level() {
      return Ed_level;
}
public void setEd_level(String ed_level) {
      Ed_level = ed_level;
}
public int getFamincome() {
      return Famincome;
}
public void setFamincome(int famincome) {
      Famincome = famincome;
}
public double getBudget() {
      return Budget;
}
public void setBudget(double budget) {
      Budget = budget;
}
public int getHours() {
      return Hours;
}
public void setHours(int hours) {
      Hours = hours;
}
public double getSkill() {
      return Skill;
}
public void setSkill(double skill) {
```

```
      Skill = skill;
}
public int getPhising() {
      return phising;
}
public void setPhising(int phising) {
      this.phising = phising;
}
public int getPRisk1() {
      return PRisk1;
}
public void setPRisk1(int risk1) {
      PRisk1 = risk1;
}
public int getPRisk2() {
      return PRisk2;
}
public void setPRisk2(int risk2) {
      PRisk2 = risk2;
}
public int getDispTrust() {
      return DispTrust;
}
public void setDispTrust(int dispTrust) {
      DispTrust = dispTrust;
}
public int getImpBvior() {
      return ImpBvior;
}
public void setImpBvior(int impBvior) {
      ImpBvior = impBvior;
}
public int getImp8() {
      return Imp8;
}
public void setImp8(int imp8) {
      Imp8 = imp8;
}
public double getTrust3() {
      return Trust3;
}
public void setTrust3(double trust3) {
      Trust3 = trust3;
}
public int getSelfE() {
      return SelfE;
}
public void setSelfE(int selfE) {
      SelfE = selfE;
}
public double getTrust() {
      return Trust;
}
public void setTrust(double trust) {
      Trust = trust;
}
public int getPRisk() {
```

```
		return PRisk;
	}
	public void setPRisk(int risk) {
		PRisk = risk;
	}
	public int getWOM1() {
		return WOM1;
	}
	public void setWOM1(int wom1) {
		WOM1 = wom1;
	}
	public int getWOM2() {
		return WOM2;
	}
	public void setWOM2(int wom2) {
		WOM2 = wom2;
	}
	public double getWOM3() {
		return WOM3;
	}
	public void setWOM3(double wom3) {
		WOM3 = wom3;
	}
	public double getWOM4() {
		return WOM4;
	}
	public void setWOM4(double wom4) {
		WOM4 = wom4;
	}
	public double getWOM5() {
		return WOM5;
	}
	public void setWOM5(double wom5) {
		WOM5 = wom5;
	}
	public double getIKnown() {
		return IKnown;
	}
	public void setIKnown(double known) {
		IKnown = known;
	}
	public void setTimes(int times) {
		Times = times;
	}
	public int getTimes() {
		return Times;
	}
	public void setSpend(int spend) {
		Spend = spend;
	}
	public int getSpend() {
		return Spend;
	}
	public void setTimeScal(String timeScal) {
		TimeScal = timeScal;
	}
	public String getTimeScal() {
```

```
		return TimeScal;
	}
	public void setSpendSca(String spendSca) {
		SpendSca = spendSca;
	}
	public String getSpendSca() {
		return SpendSca;
	}
	public String getGender() {
		return Gender;
	}
	public void setGender(String gender) {
		Gender = gender;
	}
	public double getAge() {
	return age;
	}
	public void setAge(double age) {
	this.age = age;
	}
	public void setStudent(String student) {
		// TODO Auto-generated method stub
	}
	public String getStudent() {
		return Student;
	}

	@ScheduledMethod(start = 1, interval = 1, shuffle=true)
	@Override
	public void step() {
      // Get the context in which the consumer resides.
			surf(); //move around the grid to find a website for
buy something
			//look for the around consumers

			lookAround(); //evaluate agent intention buying
according the desicion rules
			evaluateown();
		refine(); // refine its intention by interaction with other
agents
			update(); // properties are updated by adaptation

		}


	public void surf() {
		// The consumer is aware of its location in the continuous
space and
		// which web site patch it is on

		// Get the context in which the agent is residing
		Context context = ContextUtils.getContext(this);
	// The agent is aware of its location in the continuous space and
			// which web page it is on
			// Get the context in which the agent is residing
			// Get the patch grid from the context
```

```
                  Grid patch = (Grid) context.getProjection("Simple
Grid");
                  // Get the continuous space from the context
                  ContinuousSpace space = (ContinuousSpace)
context.getProjection("Continuous Space");

                  NdPoint point = space.getLocation(this);  // Get the
agent's point coordinate from the space
                  double x = point.getX();                  // The x
coordinate on the 2D continuous space
                  double y = point.getY();      // The y coordinate on
the 2D continuous space

                  // Randomly change the current heading plus or minus 50
degrees
                  double sgn = Math.random() - 0.5;  // a value between -
0.5 and 0.5
                  double heading = this.getHeading();
                  if (sgn > 0)
                    this.setHeading(heading + Math.random()*50);
                  else
                        this.setHeading(heading - Math.random()*50);



                  // Move the agent on the space by one unit according to
its new heading
                  space.moveByVector(this, 1,
Math.toRadians(heading),0,0);

                  // Move the agent to its new patch (note the patch may
not actually change)
                  patch.moveTo(this, (int)x, (int)y);
      }

      public void evaluateown(){

            double nonelikelihood = 0; //willingness for non buying
            double lowlikelihood = 0 ;  //willingness for buying from 1
to 5 times
            double medlikelihood = 0; //willingness for buying from 6 to
20 times
            double highlikelihood = 0; //willingness for buying more than
20 times

          //obtain consumer relevant parameters for the dependant
variable TIMES
          double wom3 = this.getWOM3();
          double wom4 = this.getWOM4();
          double wom5 = this.getWOM5();
          double Iknown = this.getIKnown();
          double age = this.getAge();
          double skill =  this.getSkill();
          double trustSum =  this.getTrust();
          double budget =  this.getBudget();
          int hours =  this.getHours();
```

```
        // rules for consumer to consumer interaction
           // Node 65
            if (wom3<= 1){
                  nonelikelihood = 0.7059 ;
                  lowlikelihood =  0.2917;
                  medlikelihood =  0.00;
                  highlikelihood =  0.00;}
            // Node 69
            if (wom3 > 1  &&  wom3 <= 4 &&  Iknown <= 2){
                  nonelikelihood = 0.636364;
                  lowlikelihood =  0.3273;
                  medlikelihood =  2.73;
                  highlikelihood =  0.0091;}
            // Node 70
            if (wom3 > 1  && wom3 <= 4 &&  Iknown> 2){
                  nonelikelihood = 0.3231;
                  lowlikelihood =  0.538462;
                  medlikelihood =  0.1231;
                  highlikelihood = 0.0154;}
      // Node 72
            if (wom3 > 4  &&  wom3 <= 5  &&  ((age >=16 && age <=20) ||
age >= 52)){
                  nonelikelihood = 0.509804;
                  lowlikelihood = 0.4510;
                  medlikelihood = 0.0392;
                  highlikelihood = 0.00;}
            // Node 74
            if (wom3 > 5 &&  wom5 <= 6){
                  nonelikelihood = 0.0;
                  lowlikelihood = 0.50;
                  medlikelihood = 0.50;
                  highlikelihood = 0.00;}
            // Node 75
            if (wom3 > 4  &&  wom3 <= 5  &&  age >= 21  &&  age <= 51 &&
trustSum <= 8){
                  nonelikelihood  = 0.3448;
                  lowlikelihood =  0.655172;
                  medlikelihood = 0.00;
                  highlikelihood = 0.00;}
            // Node 76
            if (wom3 > 4  &&  wom3 <= 5  &&  age >= 21  &&  age <= 51 &&
trustSum > 8){
                  nonelikelihood  = 0.0857;
                  lowlikelihood =  0.571429;
                  medlikelihood = 0.3429;
                  highlikelihood = 0.00;}
            //* Node 79
            if (wom3 > 5  && wom5 <= 6 &&  budget <= 200){
                  nonelikelihood  = 0.4667;
                  lowlikelihood = 0.488889;
                  medlikelihood = 0.0444;
                  highlikelihood = 0.00;}
            //* Node 81
            if (wom3 > 5 && wom5 <= 6 && budget > 200 &&  hours <= 3){
                  nonelikelihood  = 0.30;
                  lowlikelihood = 0.650000;
                  medlikelihood = 0.05;
```

```
                highlikelihood = 0.00;}
            // Node 82
            if (wom3 > 5 && wom5 <= 6 && budget > 200 &&  hours > 3){
                nonelikelihood  = 0.0690;
                lowlikelihood = 0.586207;
                medlikelihood = 0.3103;
                highlikelihood = 0.0345;}


            //updates the likelihood measures in the actual consumer
agent
            this.setNoneBuyerLikelihood(nonelikelihood);
            this.setMedBuyerLikelihood(medlikelihood);
            this.setLowBuyerLikelihood(lowlikelihood);
            this.setHighBuyerLikelihood(highlikelihood);

            //rules for agent to web site interactions
              //node 30 rule
              if (wom4<= 1){
                nonelikelihood = 0.85 ;
                lowlikelihood = 0.1250;
                medlikelihood =  0.025;
                highlikelihood =  0.0;}
              // node 31 rule
              if (wom4 > 1 &&  wom4 <= 2){
                nonelikelihood = 0.5333 ;
            lowlikelihood =  0.4333;
            medlikelihood =  0.0;
            highlikelihood = 0.0333;}
              // node 32 rule
              if (wom4 > 2 &&  wom4 <= 3){
                nonelikelihood = 0.5714 ;
                lowlikelihood = 0.3333;
                medlikelihood =  0.0952;
                highlikelihood = 0.00;}
              // node 36 rule
              if (wom4 > 6){
                nonelikelihood = 0.1852 ;
                lowlikelihood =  0.5556;
                medlikelihood =  0.2407;
                highlikelihood = 0.0185;}
              // node 37 rule
              if (wom4 > 3 && wom4 <=4 && Iknown <=2){
                nonelikelihood = 0.64 ;
                lowlikelihood = 0.3467;
                medlikelihood =  0.0133;
                highlikelihood = 0.00;}
              // node 38 rule
              if (wom4 > 3  &&  wom4 <= 4 &&  Iknown > 2){
                nonelikelihood = 0.2895 ;
                lowlikelihood =   0.6316;
                medlikelihood =  0.0789;
                highlikelihood = 0.00;}
                // Node 40
            if (wom4 > 4  && wom4 <= 5  &&  ((age >=16 && age <=20) ||
(age > 52))){
                nonelikelihood = 0.522727;
```

```
                  lowlikelihood =  0.4733;
                  medlikelihood =  0.0;
                  highlikelihood =  0.00;}
                // node 41 rule
                if (wom4 > 5  &&  wom4 <= 6 &&  skill <= 3){
                  nonelikelihood = 0.5227 ;
                  lowlikelihood = 0.4773;
                  medlikelihood =  0.0;
                  highlikelihood = 0.0;}
                // node 42 rule
                if (wom4 > 5  &&  wom4 <= 6 &&  skill > 3){
                  nonelikelihood = 0.0769 ;
                  lowlikelihood =  0.4615;
                  medlikelihood = 0.4615;
                  highlikelihood =  0.0;}
                // Node 43 rule/
                if (wom4  > 4  &&  wom4 <= 5  &&  age >= 21  &&  age <=
43 &&  trustSum <= 8){
                  nonelikelihood = 0.4054 ;
                  lowlikelihood = 0.5405;
                  medlikelihood =  0.0541;
                  highlikelihood = 0.0;}
                // Node 44* rule
                if (wom4 > 4  &&  wom4 <= 5 && age >=21  &&  age<=43 &&
trustSum > 8){
                  nonelikelihood = 0.0732 ;
                  lowlikelihood =   0.7561;
                  medlikelihood = 0.1463;
                  highlikelihood =0.0244;}
            //updates the likelihood measures in the actual consumer
agent
                  nonelikelihood =  (nonelikelihood +
this.getNoneBuyerLikelihood())/2;
                  lowlikelihood =  (lowlikelihood +
this.getLowBuyerLikelihood())/2;
                  medlikelihood =  (medlikelihood +
this.getMedBuyerLikelihood())/2;
                  highlikelihood =  (highlikelihood +
this.getHighBuyerLikelihood())/2;
            this.setNoneBuyerLikelihood(nonelikelihood);
            this.setMedBuyerLikelihood(medlikelihood);
            this.setLowBuyerLikelihood(lowlikelihood);
            this.setHighBuyerLikelihood(highlikelihood);
            System.out.println("none" + nonelikelihood + "low" +
lowlikelihood +  "med" + medlikelihood);
      }

private void lookAround() {
            // TODO Auto-generated method stub
            //consumer to consumer interaction
            // a consumer select a number of neighbor according to a
relative distance
            // for each member of the neighborhood obtain the positive
experience in buying from the web site
            // follow the rules of behavior according to the
classification tree
            /* Node 65*/
```

```
            //int countReviews;
      Context context = ContextUtils.getContext(this);
                  // Get the context in which the agent is residing
                  // Get the patch grid from the context
      Grid patch = (Grid) context.getProjection("Simple Grid");
                  // Get the continuous space from the context
      ContinuousSpace space = (ContinuousSpace)
context.getProjection("Continuous Space");
      //get the neighbors in the web environment with a distance of 2
      GridPoint pointW = patch.getLocation(this);
      int x = pointW.getX();   // The x-ccordinate of the consumer's
current patch
      int y = pointW.getY();   // The y-ccordinate of the consumer's
current patch
      int countneighbor = 0;
      int sumwom1 = 0;
      int sumwom2 = 0;
      int sumtimes = 0;
      double avgwom1 = 0;
      double avgwom2 = 0;
      double avgtimes = 0;
      Consumer neighbor = null;

      for (int i = -2; i<=2; i++){
        for (int j = -2; j <=2; j++){
            for (Object o : patch.getObjectsAt(x+i,y+j)){
                  if (o instanceof Consumer)
                        neighbor = (Consumer)o;
            }
            // If there is a neighbor, then obtain its properties
            if (neighbor != null ){
                  int times = neighbor.getTimes();
                  int wom1 = neighbor.getWOM1();
                  int wom2 = neighbor.getWOM2();

                  // only consider those influent neighbors
                  if (wom1 >=4 || wom2>=4){
                        sumtimes  = sumtimes + times;
                        sumwom1 = sumwom1 + wom1;
                        sumwom2 = sumwom2 +  wom2;
                        countneighbor ++;
                  }
        }
       }
      }
      if (countneighbor > 0) {
            avgwom1 = ( sumwom1 / countneighbor) / 7;
            avgwom2 = (sumwom2 / countneighbor) / 7;
            avgtimes = sumtimes / countneighbor;
            if (avgtimes ==0){ //negative experiences decrees wom3
              this.setWOM3(this.getWOM3()- 1*((avgwom1 +
avgwom2)/2)*0.33);
              this.setWOM5(this.getWOM5()- 1*((avgwom1 +
avgwom2)/2)*0.33);
            }
            else if (avgtimes <=5) {
```

```
                  this.setWOM3(this.getWOM3()+ 1 *((avgwom1 + 
avgwom2)/2)*0.33);
                  this.setWOM5(this.getWOM5()+ 1*((avgwom1 + 
avgwom2)/2)*0.33);
            }
            else
                  if (avgtimes <=20) {
                        this.setWOM3(this.getWOM3()+ 2*((avgwom1 + 
avgwom2)/2)*0.33);
                        this.setWOM5(this.getWOM5()+ 2*((avgwom1 + 
avgwom2)/2)*0.33);
                  }
                  else {
                        this.setWOM3(this.getWOM3()+ 3*((avgwom1 + 
avgwom2)/2)*0.33);
                        this.setWOM5(this.getWOM5()+ 3*((avgwom1 + 
avgwom2)/2)*0.33);
                  }
            System.out.println("vecinos: " + countneighbor + "wom3" + 
this.getWOM3() +  "wom5" + this.getWOM5());
      }
      }

private void refine() {


}

private void update(){ //update according to the GUI parameters
      Parameters p = RunEnvironment.getInstance().getParameters();
      double param1 =  (Double)p.getValue("iknownincrement");
      if (param1 > 0)
        param1 = 1/param1;
      double param2 =  (Double)p.getValue("skillincrement");
      if (param2 > 0)
            param2 = 1/param2;
      double Iknown1 =  this.getIKnown();
      if (Iknown1 <4)
            Iknown1 = Iknown1 + param1;
      this.setIKnown(Iknown1);
      double Skill1 = this.getSkill();
      if (Skill1 < 4)
            Skill1  =  Skill1  +  param2;
      this.setSkill(Skill1);
      double param3 = (Double)p.getValue("ageincrement");
      double Age1 = this.getAge();
      if (param3 > 0)
            param3 = 1/param3;
      if (Age1 <52)
      Age1 = Age1 + param3;
      this.setAge(Age1);
      double param4 =(Double)p.getValue ("trustIncrement");
      double Trust1 = this.getTrust();
      if (param4 >0)
            param4 = 1/param4;
      if (Trust1<14)
            Trust1 = Trust1 + param4;
```

```
	this.setTrust(Trust1);

	//update the web page score and count reviews
	// Get the web site's current patch
	Context context = ContextUtils.getContext(this);
	Grid patch = (Grid) context.getProjection("Simple Grid");
	GridPoint pointW = patch.getLocation(this);

	int xW = pointW.getX();   // The x-ccordinate of the consumer's
current patch
	int yW = pointW.getY();   // The y-ccordinate of the consumer's
current patch

	// begins the interaction with the web site
	// Find the website at the patch and rate
	WebSite website = null;
	for (Object o : patch.getObjectsAt(xW,yW)){
		if (o instanceof WebSite)
			website = (WebSite)o;
	}
	// If there is a website, then obtain its reviews
	if (website != null ){
		//obtain the count reviews
		int countReviews;
	    countReviews = website.getCountReviews();
	    //increment wom4 due the countreviews
	    if (countReviews <=5)

	      this.setWOM4(this.getWOM4()+ 0 * 0.0333);
	    else
	      if (countReviews <=10)

			this.setWOM4(this.getWOM4()+ 1 * 0.0333);
	      else
			if (countReviews <=50)

				this.setWOM4(this.getWOM4()+ 2 * 0.0333);
			else

				this.setWOM4(this.getWOM4()+ 3 * 0.0333);
	    //consumer to consumer interaction
	    int countneighbor = 0;
	      int sumwom1 = 0;
	      int sumwom2 = 0;
	      int sumtimes = 0;
	      double avgwom1 = 0;
	      double avgwom2 = 0;
	      double avgtimes = 0;
	      Consumer neighbor = null;

	      for (int i = -2; i<=2; i++){
	        for (int j = -2; j <=2; j++){
			for (Object o : patch.getObjectsAt(xW+i,yW+j)){
				if (o instanceof Consumer)
					neighbor = (Consumer)o;
			}
			// If there is a neighbor, then obtain its properties
```

```
                  if (neighbor != null ){
                        int times = neighbor.getTimes();
                        int wom1 = neighbor.getWOM1();
                        int wom2 = neighbor.getWOM2();

                        // only consider those influent neighbors
                        if (wom1 >=4 || wom2>=4){
                              sumtimes  = sumtimes + times;
                              sumwom1 = sumwom1 + wom1;
                              sumwom2 = sumwom2 +  wom2;
                              countneighbor ++;
                        }
              }
             }
            }
            if (countneighbor > 0) {
                  avgwom1 = ( sumwom1 / countneighbor) / 7;
                  avgwom2 = (sumwom2 / countneighbor) / 7;
                  avgtimes = sumtimes / countneighbor;
                  if (avgtimes ==0){ //negative experiences decrees wom3
                        //if (this.getWOM3()<7)
                              this.setWOM3(this.getWOM3()- 1*((avgwom1 +
avgwom2)/2)*0.033);
                        //if (this.getWOM5()<7)
                    this.setWOM5(this.getWOM5()- 1*((avgwom1 +
avgwom2)/2)*0.033);
                  }
                  else if (avgtimes <=5) {
                        //if (this.getWOM3()<7)
                        this.setWOM3(this.getWOM3()+ 1 *((avgwom1 +
avgwom2)/2)*0.033);
                  //    if (this.getWOM5()<7)
                        this.setWOM5(this.getWOM5()+ 1*((avgwom1 +
avgwom2)/2)*0.033);
                  }
                  else
                        if (avgtimes <=20) {
                        //    if (this.getWOM3()<7)
                              this.setWOM3(this.getWOM3()+ 2*((avgwom1 +
avgwom2)/2)*0.033);
                              //if (this.getWOM5()<7)
                              this.setWOM5(this.getWOM5()+ 2*((avgwom1 +
avgwom2)/2)*0.033);
                        }
                        else {
                        //    if (this.getWOM3()<7)
                              this.setWOM3(this.getWOM3()+ 3*((avgwom1 +
avgwom2)/2)*0.33);
                        //    if (this.getWOM5()<7)
                              this.setWOM5(this.getWOM5()+ 3*((avgwom1 +
avgwom2)/2)*0.33);
                        }
                  System.out.println("vecinos: " + countneighbor + "wom3"
+ this.getWOM3() +  "wom5" + this.getWOM5());
            }

            //this.setWOM3(this.getWOM3()+ 0.0333);
```

```
            //this.setWOM5(this.getWOM5()+ 0.0333);
            //obtain consumer relevant parameters for the dependant
variable TIMES
            double nonelikelihood  = this.getNoneBuyerLikelihood();
//willingness for non buying
            double lowlikelihood  = this.getLowBuyerLikelihood();
//willingness for buying from 1 to 5 times
            double medlikelihood =  this.getMedBuyerLikelihood();
//willingness for buying from 6 to 20 times
            double highlikelihood =  this.getHighBuyerLikelihood();
          double wom3 = this.getWOM3();
          double wom4 = this.getWOM4();
          double wom5 = this.getWOM5();
          double Iknown = this.getIKnown();
          double age = this.getAge();
          double skill =  this.getSkill();
          double trustSum =  this.getTrust();
          double budget =  this.getBudget();
          int hours =  this.getHours();

        // rules for consumer to consumer interaction
           // Node 65
            if (wom3<= 1){
                  nonelikelihood = 0.7059 ;
                  lowlikelihood =  0.2917;
                  medlikelihood =  0.00;
                  highlikelihood =  0.00;}
            // Node 69
            if (wom3 > 1  &&  wom3 <= 4 &&  Iknown <= 2){
                  nonelikelihood = 0.636364;
                  lowlikelihood =  0.3273;
                  medlikelihood =  2.73;
                  highlikelihood =  0.0091;}
            // Node 70
            if (wom3 > 1  && wom3 <= 4 &&  Iknown> 2){
                  nonelikelihood = 0.3231;
                  lowlikelihood =  0.538462;
                  medlikelihood =  0.1231;
                  highlikelihood = 0.0154;}
      // Node 72
            if (wom3 > 4  &&  wom3 <= 5  &&  ((age >=16 && age <=20) ||
age >= 52)){
                  nonelikelihood = 0.509804;
                  lowlikelihood = 0.4510;
                  medlikelihood = 0.0392;
                  highlikelihood = 0.00;}
            // Node 74
            if (wom3 > 5 &&  wom5 <= 6){
                  nonelikelihood = 0.0;
                  lowlikelihood = 0.50;
                  medlikelihood = 0.50;
                  highlikelihood = 0.00;}
            // Node 75
            if (wom3 > 4  &&  wom3 <= 5  &&  age >= 21  &&  age <= 51 &&
trustSum <= 8){
                  nonelikelihood  = 0.3448;
                  lowlikelihood =  0.655172;
```

```
                medlikelihood = 0.00;
                highlikelihood = 0.00;}
          // Node 76
          if (wom3 > 4  &&  wom3 <= 5  &&  age >= 21  &&  age <= 51 &&
trustSum > 8){
                nonelikelihood  = 0.0857;
                lowlikelihood =  0.571429;
                medlikelihood = 0.3429;
                highlikelihood = 0.00;}
          //* Node 79
          if (wom3 > 5  && wom5 <= 6 &&  budget <= 200){
                nonelikelihood  = 0.4667;
                lowlikelihood = 0.488889;
                medlikelihood = 0.0444;
                highlikelihood = 0.00;}
          //* Node 81
          if (wom3 > 5 && wom5 <= 6 && budget > 200 &&  hours <= 3){
                nonelikelihood  = 0.30;
                lowlikelihood = 0.650000;
                medlikelihood = 0.05;
                highlikelihood = 0.00;}
          // Node 82
          if (wom3 > 5 && wom5 <= 6 && budget > 200 &&  hours > 3){
                nonelikelihood  = 0.0690;
                lowlikelihood = 0.586207;
                medlikelihood = 0.3103;
                highlikelihood = 0.0345;}


          //updates the likelihood measures in the actual consumer
agent
          this.setNoneBuyerLikelihood(nonelikelihood);
          this.setMedBuyerLikelihood(medlikelihood);
          this.setLowBuyerLikelihood(lowlikelihood);
          this.setHighBuyerLikelihood(highlikelihood);

          //rules for agent to web site interactions
              //node 30 rule
              if (wom4<= 1){
                nonelikelihood = 0.85 ;
                lowlikelihood = 0.1250;
                medlikelihood =  0.025;
                highlikelihood =  0.0;}
              // node 31 rule
              if (wom4 > 1 &&  wom4 <= 2){
                nonelikelihood = 0.5333 ;
          lowlikelihood =  0.4333;
          medlikelihood =  0.0;
          highlikelihood = 0.0333;}
              // node 32 rule
              if (wom4 > 2 &&  wom4 <= 3){
                nonelikelihood = 0.5714 ;
                lowlikelihood = 0.3333;
                medlikelihood =  0.0952;
                highlikelihood = 0.00;}
              // node 36 rule
              if (wom4 > 6){
```

```
                  nonelikelihood = 0.1852 ;
                  lowlikelihood =  0.5556;
                  medlikelihood =  0.2407;
                  highlikelihood = 0.0185;}
                // node 37 rule
                if (wom4 > 3 && wom4 <=4 && Iknown <=2){
                  nonelikelihood = 0.64 ;
                  lowlikelihood = 0.3467;
                  medlikelihood =  0.0133;
                  highlikelihood = 0.00;}
                // node 38 rule
                if (wom4 > 3  &&  wom4 <= 4 &&  Iknown > 2){
                  nonelikelihood = 0.2895 ;
                  lowlikelihood =   0.6316;
                  medlikelihood =  0.0789;
                  highlikelihood = 0.00;}
                  // Node 40
            if (wom4 > 4  && wom4 <= 5  &&  ((age >=16 && age <=20) ||
(age > 52))){
                  nonelikelihood = 0.522727;
                  lowlikelihood =  0.4733;
                  medlikelihood =  0.0;
                  highlikelihood =  0.00;}
                // node 41 rule
                if (wom4 > 5  &&  wom4 <= 6 &&  skill <= 3){
                  nonelikelihood = 0.5227 ;
                  lowlikelihood = 0.4773;
                  medlikelihood =  0.0;
                  highlikelihood = 0.0;}
                // node 42 rule
                if (wom4 > 5  &&  wom4 <= 6 &&  skill > 3){
                  nonelikelihood = 0.0769 ;
                  lowlikelihood =  0.4615;
                  medlikelihood = 0.4615;
                  highlikelihood =  0.0;}
                // Node 43 rule/
                if (wom4  > 4  &&  wom4 <= 5  &&  age >= 21  &&  age <=
43 &&  trustSum <= 8){
                  nonelikelihood = 0.4054 ;
                  lowlikelihood = 0.5405;
                  medlikelihood =  0.0541;
                  highlikelihood = 0.0;}
                // Node 44* rule
                if (wom4 > 4  &&  wom4 <= 5 && age >=21  &&  age<=43 &&
trustSum > 8){
                  nonelikelihood = 0.0732 ;
                  lowlikelihood =   0.7561;
                  medlikelihood = 0.1463;
                  highlikelihood =0.0244;}
            //updates the likelihood measures in the actual consumer
agent
                  nonelikelihood =  (nonelikelihood +
this.getNoneBuyerLikelihood())/2;
                  lowlikelihood =  (lowlikelihood +
this.getLowBuyerLikelihood())/2;
                  medlikelihood =  (medlikelihood +
this.getMedBuyerLikelihood())/2;
```

```
                  highlikelihood =  (highlikelihood +
this.getHighBuyerLikelihood())/2;
            this.setNoneBuyerLikelihood(nonelikelihood);
            this.setMedBuyerLikelihood(medlikelihood);
            this.setLowBuyerLikelihood(lowlikelihood);
            this.setHighBuyerLikelihood(highlikelihood);
            System.out.println("none" + nonelikelihood + "low" +
lowlikelihood +  "med" + medlikelihood);

          //calculate the cummulative probability
             nonelikelihood = this.getNoneBuyerLikelihood();
              lowlikelihood = nonelikelihood +
this.getLowBuyerLikelihood();
             medlikelihood = lowlikelihood +
this.getMedBuyerLikelihood();
            highlikelihood = medlikelihood +
this.getHighBuyerLikelihood();
      //calculate the dependent variable times
      double level = Math.random();
      int times = 0;
      if (level <= nonelikelihood)
         times = 0;
      else
            if (level <= lowlikelihood)
                     times  = (int) Math.floor(Math.random())+ 5;
            else
                  if (level <= medlikelihood)
                        times = (int)  Math.floor(Math.random() * 14) +
6;
                  else
                        times = (int) Math.floor(Math.random() * 19) +
21;
      //update property times in consumer agent
      this.setTimes(times);
      //put reviews on the web site based on the number of purchased made

            if (this.getTimes()==0)
                countReviews = website.getCountReviews()- 1;
            else
                  if (this.getTimes() <=5)
                        countReviews = this.getTimes()+ 1;
                  else if (this.getTimes() <= 20)
                        countReviews = this.getTimes()+ 3;
                  else
                        countReviews = this.getTimes()+ 10;
            website.setCountReviews(countReviews);
            website.update();
      }
}


 public int isNonbuyer() {
    if (this.getTimes() == 0)
      return 1;
    else
      return 0;
 }
```

```
 public int isLowbuyer() {
          if (this.getTimes() > 0 && this.getTimes() <= 5)
            return 1;
          else
            return 0;
       }
 public int isMediumbuyer() {
          if (this.getTimes() > 5 && this.getTimes() <= 20)
            return 1;
          else
            return 0;
       }
 public int isHighbuyer() {
          if (this.getTimes() > 20 )
            return 1;
          else
            return 0;
       }

 public int isBuyer(){
       if (this.getTimes()>0)
             return 1;
       else
             return 0;
 }



}
```

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