THE INFLUENCE OF KNOWLEDGE-BASED E-COMMERCE PRODUCT RECOMMENDER AGENTS ON ONLINE-CONSUMER DECISION MAKING PROCESS

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ABSTRACT

THE INFLUENCE OF KNOWLEDGE-BASED E-COMMERCE PRODUCT RECOMMENDER AGENTS ON ONLINE-CONSUMER DECISION MAKING PROCESS

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Online retailers are providing large amount of products over internet for potential customers. Given the opportunity of accessing vast amount of products online, customers usually encounter difficulties to choose the right product or service for themselves. Obtaining advice from internet is both time consuming and most of time not reliable. Therefore, intelligent software is needed to act on behalf of customer in such situations. Recommender systems (agents) are intelligent software providing easily accessible, high-quality recommendations for online consumers. They either track online customer behavior implicitly or obtain information from the customer explicitly and provide the products or services in which customer might be interested. By utilizing such systems, online retailers not only increase their sales but also assist their customers in finding the products or services. This study has assessed the influence of knowledge-based recommender systems on online-consumer decision making process. Shopping duration, purchase of intended item, effort spent in searching intended product and decision quality of online consumer have been assessed by exposing the participants to knowledge-based recommender system which has been integrated to one of the online shopping systems developed in the scope of this study. Only objective measures have been utilized in this research; that is, shopping system log data have been used to measure the influence of recommender agents on consumer decision making process. Study findings have showed that knowledge-based recommender systems improve consumer decision making process by reducing the shopping duration and effort spent in searching suitable products. Also, it has been found that decision quality and the number of consumers who purchase the intended item increase in the existence of such systems. Results of this study provide additional evidences of the potential benefits of integrating such systems to online web stores.

Keywords: Recommender Systems, Recommender Agents, Consumer Decision Process

ÖZ

E-TİCARETTE KULLANILAN BİLGİ-TABANLI ÖNERİ SİSTEMLERİNİN ONLİNE MÜŞTERİLERİN KARAR SÜRECİNE ETKİLERİ

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Online satış yapan kurumlar, potansiyel müşteriler için internet üzerinde geniş bir ürün yelpazesi sunuyorlar. Bu geniş ürün yelpazesiyle karşılaşan müşteriler çoğu zaman kendileri için en uygun olan ürünü seçerken sıkıntı yaşıyorlar. İnternet üzerinden ürüne ilişkin tavsiye almak ise hem güvenilir değil hem de uzun zaman alıyor. Bu yüzden bu tür durumlarda müşteri yararına harekete geçecek bazı akıllı yazılımlara ihtiyaç duyuluyor. Recommender sistemler online müşterilere yüksek kalitede ve kolay erişilebilir tavsiyeler sunan akıllı yazılımlardır. Recommender sistemler ya online müşteri davranışlarını tamamen takip eder ya da müşterilerden açıkça bilgi edinir ve müşterilerin ilgilenme olasılıkları olan ürün veya servisleri onlara sunar. Bu tip sistemleri kullanarak online satıcılar sadece satışlarını artırmıyor ayrıca müşterilerinin kriterlerine uygun ürünü veya hizmeti bulmakta yardım da sağlıyorlar. Bu çalışma e-ticarette kullanılan recommender sistemlerinin online müşterilerin karar sürecine etkilerini değerlendirmeyi amaçlar. Bu çalışma kapsamında geliştirilmiş, içerisine öneri systemi entegre edilmiş bir sistem yardımıyla online müşterinin karar süresi, müşteri tarafından yapılan araştırma miktarı, kararının kalitesi ve yine müşteri tarafından arzu edilen ürünün alışı değerlendirildi. Bu çalışma yalnızca objektif metod ve ölçümleri kullanmıştır; yani alışveriş sisteminin takip etmiş olduğu kayıtlar, öneri sisteminin tüketicinin karar verme sürecindeki etkisini ölçmede kullanılmıştır. Çalışma sonuçları gösteriyor ki bilgi tabanlı öneri sistemleri alış-veriş süresini ve uygun ürün arayışındaki çabayı azaltarak müşterinin karar verme sürecini geliştirir. Ayrıca, bu tip sistemlerin kullanıldığı ortamlarda istendik ürünü satın alan müsteri sayısı ve karar kalitesinin arttığı da saptanmıştır. Bu çalışmanın sonuçları online ticaret web sitelerine bu tür akıllı sistemleri entegre etmenin ekstra yararlarıyla ilgili kanıtlar sunar.

Anahtar Kelimeler: Satış Öneri Sistemleri, Online Alış-Veriş, Tüketici Karar Süreci

This thesis is dedicated to:

To my wife SEMA YILDIZ HUSEYNOVA

&

My Family

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LIST OF ABBREVIATIONS

ASP	Active Server Pages
IS	Information Systems
METU	Middle East Technical University
NRA	Non-Recommender Agent
RA	Recommender Agent
RS	Recommender System
URL	Uniform Resource Locator

CHAPTER I

INTRODUCTION

This is an introduction chapter which makes brief introduction to the recommender systems. In this chapter the study objectives, the research questions, research scope and the thesis structure are given.

1.1 Introduction

In ten years time period, the amount of internet users has increased substantially. Statistics of worldwide internet users are shown in Table 1. As internet world stat shows, worldwide internet users' number increased approximately 5 times from the year 2000 to 2011. While this number is about 361 million in 2000, it is calculated as approximately 2.267 billion for the year 2011. Now, it is determined that the 32.7% of the world population uses internet.

As a consequence of this increase, merchants being aware of potential customers over internet have started to provide goods online. For merchants providing goods over internet is not a competitive advantage anymore; however, it is a must for the survival in today's business environment.

Table 1 - Internet Usage Data around World (source: Internet World Stats)

World Regions	Population (2011 Est.)	Internet Users Dec. 31, 2000	Internet Users Latest Data	Penetration (% population)	Growth 2000-2011	% of Table
Africa	1,037,524,058	4,514,400	139,875,242	13.5%	2,988.4%	6.2%
Asia	3,879,740,877	114,304,000	1,016,799,076	26.2%	789.6%	44.8%
Europe	816,426,346	105,096,093	500,723,686	61.3%	376.4%	22.1%
Middle East	216,258,843	3,284,800	77,020,995	35.6%	2,244.8%	3.4%
N. America	347,394,870	108,096,800	273,067,546	78.6%	152.6%	12.0%
S. America	597,283,165	18,068,919	235,819,740	39.5%	1,205.1%	10.4%
Oceania	35,426,995	7,620,480	23,927,457	67.5%	214.0%	1.1%
WORLD	**6,930,055,154**	**360,985,492**	**2,267,233,742**	**32.7%**	**528.1%**	100%

Figure 1 shows the estimated online retail sales for USA from the year 2009 to 2014. Forrester Research estimates that online sales will reach to 249 billion dollars in USA by the year of 2014 and this figure is predicted to be 156 billion dollars for Western Europe.

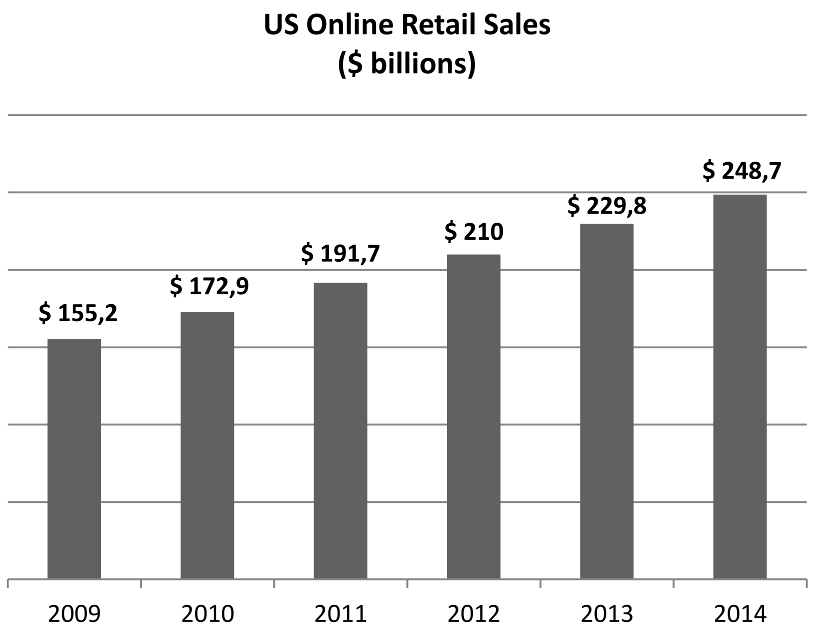

Figure 1 - US Online Retail Sales (Forrester Research)

Retailers who are aware of the opportunity of online trading are now providing large amount of products over internet for potential customers in order to increase their revenue. By making products available for online purchase, merchants now can reach customers worldwide very easily with a very low cost. For example, a customer in China can easily make transaction with a seller in USA via eBay.com which is a quite famous online merchant on the web and transportation of the products is handled by the global transportation companies to the door of the customer.

On the other hand, when customers are given the opportunity of accessing vast amount of products over internet, they encounter difficulties to choose right product or service for themselves among so many different options most of the time. Furthermore, since they are shopping online, they have no chance to ask for an advice to a sales representative about the products and services which meet their needs best. Without any kind of professional advice related to the products and services, online customers do not know which product fulfills their needs best most of the time. Customers who try to obtain advice from internet have realized that obtaining information from the web is both time consuming and not reliable most of time. Therefore, some kind of intelligent software is needed to act on behalf of customer in such situations. There exist recommender systems which exactly fulfill this need on online trade.

What is "Recommender Systems"? Most of the internet users have experienced some kind of recommender systems either consciously or unconsciously. Recommender systems (agents) are intelligent software which provide easily accessible, high-quality recommendations for online consumer. Recommender systems either track online customer behavior implicitly or obtain information from the customer explicitly and provide the products or services in which customer might be interested (Jannach et. al, 2011). It is possible to see one of the types of recommender systems on one of the most famous online merchant, Amazon.com. At this web store, after clicking on the hyperlink of any product, below the item specification of that product, a module appears with a title "*What Other Items Do Customers Buy after Viewing This Item*?" Under this title, several items in which users might be interested will be listed. Another type of recommender systems asks several questions to the online customer and based on the answers to these questions, products that meet the customers' needs more accurately are offered to the users. Rather than

recommending products to the users in a random fashion, recommender agents use intelligent techniques to attract the customers' attention to the given products.
Successful implementation of the recommender systems promise to bring new trend to conduct business over internet. Recommender systems are becoming widespread on online merchants every passing day. Now, it is common to see recommender systems in well-known online merchants' websites. "Amazon" and "eBay" can be given as an example to these websites. By utilizing such systems, online retailers increase their sales and assist their customers to find the products that match their criteria. These intelligent agents not only improves customers' decision making process by reducing amount of information burden and complexity in searching but also increases consumers' decision quality by suggesting products and services in which customer might be interested (Chiasson et al., 2002). Consumers' decision effort in online shopping context is usually measured by time spent for decision giving and the extent of product search (Xiao &Benbasat 2007). Recommender agents reduce required time for customers to find suitable products and make purchase decision (Hostler et al., 2005; Pedersen, 2000). In addition, it narrows the limit of product search by decreasing the total number of products that customers will analyze (Dellaert & Haubl 2005). By integrating such intelligent software into their online store, merchants shift tedious job of screening, filtering and sorting large amount of items from user to recommender agent and customers use their saved time to make quality decisions. Online customers' switching cost from one merchant's store to another one is very low when compared with the cost of merchant's losing a potential customer. Therefore, online retailers should integrate such intelligent agents to their websites both to serve potential customers more effectively and to increase their own sales.

1.2 Objectives of the Study

Investigation of the knowledge-based e-commerce recommender systems' impact on online consumers' decision making process while conducting transaction on online stores is the primary objective of this study.

1.3 Research Questions

The following questions have been assessed in order to find an answer:

1. Does any relation exist between the use of RA and shopping duration of online consumer?
2. Does any relation exist between the use of RA and consumers' searching effort in online stores?
3. Does the use of RA have any relation with online consumer decision quality?
4. Does the use of RA help the online consumer to purchase the intended item?

1.4 Scope of the Study

Investigation boundaries of recommender agents' impact on online consumers' decision making process are limited to the constructs stated in the conceptual model. In order to test conceptual model, a simulated online store is developed. Invited users have completed web-based online shopping task. In total 223 number of university student participated in the survey.

1.5 Design of the Study

This study employs quantitative research and follows the research process which is depicted in Figure 2.

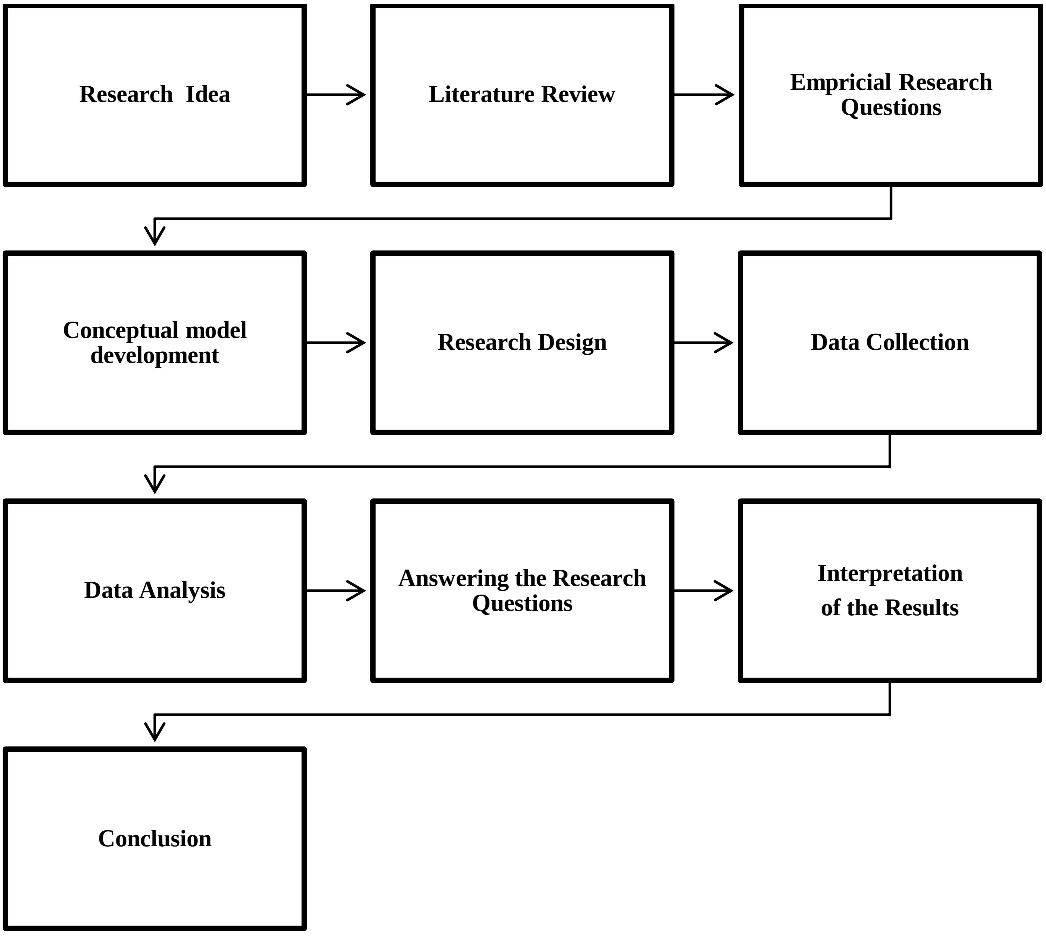

Figure 2 - Research Process

1.6 Chapters of the Thesis

This study is divided into six chapters which are mentioned below. Chapter 1 makes a brief introduction to recommender systems and defines the objectives, scope and research questions of this study.

The literature review on recommender systems is given in Chapter 2. This chapter explains each type of recommender systems and previous studies conducted on this field.

Chapter 3 mentions about research model and suggest hypotheses related to the developed model.

In Chapter 4 the methodology of this study is presented. Study settings, experimental design, developed shopping agent, data collection, data analysis and ethical clearance are mentioned in this chapter.

Chapter 5 is about the data analysis of this study. In this section, the collected data is analyzed by using necessary statistical methods and tools. Results of the statistical tests are also explained in this chapter.

Chapter 6 summarizes the study findings, contributions and limitations. In addition, this chapter suggests possible future research areas in this field.

CHAPTER II

LITERATURE REVIEW

Literature review on recommender systems is given in this chapter. Figure 3 shows the structure of this chapter. In the first subsection, different types of recommender systems are discussed. Previous studies on recommender systems are discussed in the second subsection.

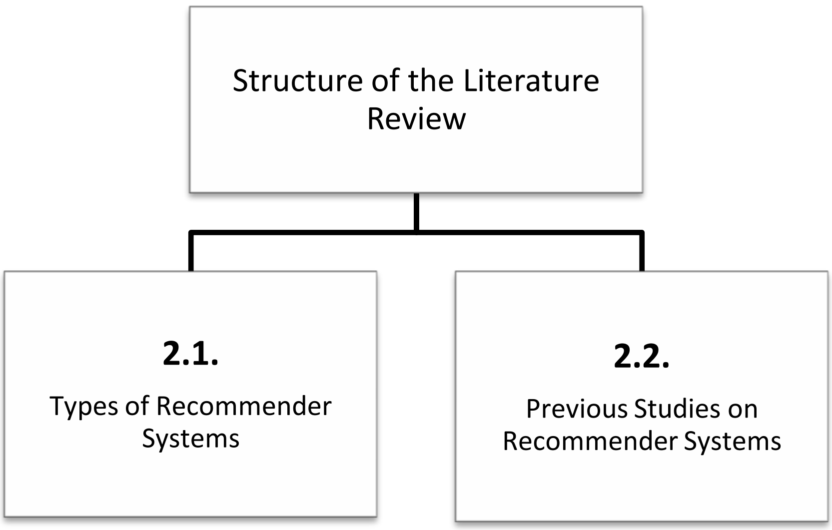

Figure 3 - Structure of the Literature Review

2.1 Types of Recommender Systems

Information overload is a common issue among the modern information society; therefore some kind of intelligent software is required to provide most relevant data according to online users' needs. Recommender systems are intelligent software which collects information from users either directly or indirectly and recommends items based on customers' usage patterns, choices, priorities and needs. RAs aim to support and guide customers during online decision making process by providing easily accessible, high quality recommendations (Jannach et al., 2011). It is possible to encounter some kind of recommender systems while purchasing a movie, music, book, electronic device or any other consumer product over internet. In Figure 4, different types of recommender systems are given. As shown in Figure 4, collaborative, content-based, knowledge-based and hybrid are the most common ones which are utilized by online retailers. Each of these recommender systems is briefly discussed in the following subsections.

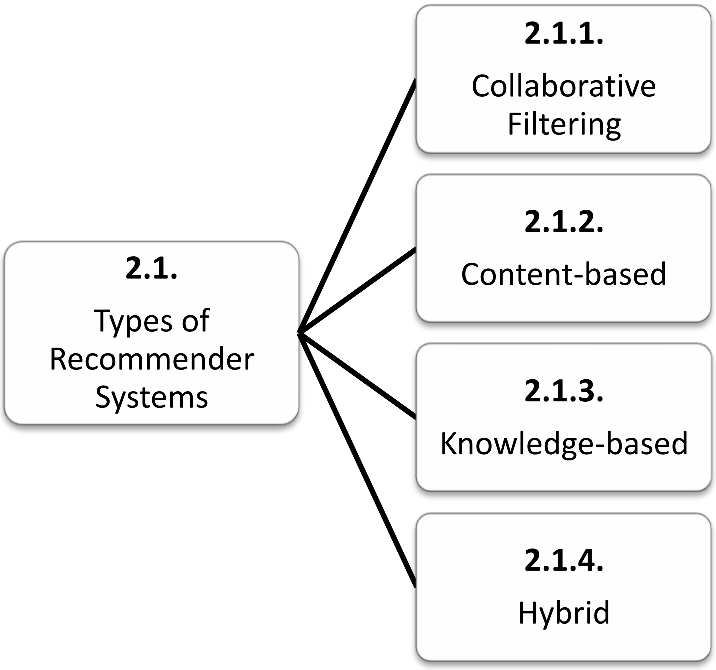

Figure 4 - Different Types of RA

2.1.1 Collaborative Filtering

In this kind of recommender system, items are suggested to the customers based on the ratings given by other users with similar tastes (Hostler et al., 2011). Actually, in our daily life, we have already used recommender systems in a different way. For example, we always share our experiences about the movies we have watched and the books we have read. In this way we find friends with similar tastes with us and after finding our reference, we always take their recommendations into consideration. People get recommendation from the people with whom they share similar tastes most of the time. The idea of collaborative filtering is actually automating the “word-of-mouth” recommendation (Shardanand & Maes, 1995). Collaborative filtering recommender agents use statistical formulas to find out customers with similar tastes. For the system’s effectiveness, customers need to rate a few items they had experience in or they should have purchasing history and by using these ratings or purchasing history, collaborative filtering finds reference customer and recommend items based on the reference customer’s rating scores. As systems’ suggestions are based on the ratings scores given to the items rather than the features of the products, suggestions presented by the system to the user might be completely different than products for which the user gave higher ratings before. Collaborative filtering requires rating for a given item in order to recommend it; that’s, content of the product has nothing to do with recommendation process. If there are few rating per item or if there are few rating per user then system cannot provide useful recommendations (Schafer et al., 2007). In collaborative filtering more and more user ratings are required as an input in order to receive useful recommendations.

2.1.2 Content-based

Content-based systems consider product features and customer profile while suggesting products to the customers. Attributes and specifications of the items that users rated are used to build customers’ interest profile and this customer profile is utilized to suggest new products to the customers (Mladenic, 1999). In other words, during the recommendation process, attributes of the user profile are matched against the content of the item.

Content-based recommenders come with several shortcomings. Firstly, some products have attributes such as quality and taste that cannot be identified easily with current technology to be matched with user profile in order to generate recommendations. Secondly, suggested products tend to be similar with previously rated products because of the systems’ tendency to recommend items scoring highly against the users’ profile. Thirdly, in general, recommender systems have a mechanism that requires users to rate items in order to receive relevant recommendations. Lastly, obtaining ratings from user is a demanding task because the user may not be willing to give feedback related to the item they had experienced (Balanbonvic & Shoham, 1997).

Content-based and collaborative RAs differ because while former focuses on products' similarity, latter focuses on customers' similarity. Another difference is that content-based recommender systems can work even with single user; that is, it does not require large user community or large amount of rating history as collaborative systems require (Jannach et al., 2011). The third difference is that in content-based systems, the recommended items probably match to user profile but the quality of the item may not meet the expected quality. However, in collaborative filtering, recommended items are based on the users' evaluation of them and those evaluations probably show the quality of the products so the quality can be considered in such systems (Funakoshi & Ohguru, 2000).

2.1.3 Knowledge-based

Collaborative-filtering systems suggests products according to the assigned ratings; that is, content of the item has nothing to do with recommendation process while content-based recommender systems suggests items or products based on user profile and item content which is automatically extracted from the item itself. In certain situations, these two approaches give undesired results. One of the situations which may not yield useful recommendations is that ratings for certain items like electronic devices might be outdated; that is, technology develops so fast that ratings for certain products might not be valid after some period of time (Jannach et al., 2011). The second situation problematic for these systems is that certain amount of ratings are required from the particular user in order for the system to understand the pattern in that user's ratings and recommend items to him/her accordingly (Burke, 2000). The problems mentioned above do not exist in the knowledge-based system since it takes into consideration neither the rating of the items nor the characteristics of the particular user. In other words, it does not need any pre-established database of user preferences and item ratings and also, this type of system is ideal for some kind of products such as cars, houses, computers and etc. since customer may consider several features of these products that differ from what other users prefer (Chun & Hong, 2001). User specifies his/her needs and system searches the database and brings the most suitable items for the user. For instance, if a customer wants to purchase a new car, he or she selects the certain feature of the car such as price, fuel efficiency, environmentally friendly and etc. By considering user entered specifications, the most suitable items are presented to the customer by the system. Customer has an ability to re-specify the feature of the desired car in order to receive different alternatives. Interaction between the customer and the system is needed to be strong in this process; in other words, customers are considered to be an integral part of knowledge-based systems (Burke, 2000). Knowledge-based systems require a very good product domain knowledge and this knowledge needs to be stored, organized and engineered in such a way that it can be easily retrieved (Chun & Hong, 2001). Static suggestion ability and knowledge engineering are the drawbacks of the knowledge-based recommender systems (Burke, 2000).

2.1.4 Hybrid

When analyzed individually, each recommender technique has its own limitations. Restricted content and feature analysis, new product problem, new customer problem, cold start and sparsity problem are just few of them (Chikhaoui et al., 2011). Common problem for most of the recommender techniques is the ramp-up problem. "Ramp-up" refers to two distinct but related problems: a user with few ratings makes categorization of that user difficult (new user problem) and item with very few ratings cannot be recommended easily (new item problem) (Burke, 2002). Put it another way, most users cannot benefit from the system unless a large number of user tastes are identified. In the same way, the system cannot provide useful recommendation for the given user unless a reasonable amount of items get rated by others (Burke, 2000). Collaborative filtering technique suffers from the ramp-up problem mentioned above. Start-up problems of content-based technique are that they need to have enough user ratings in order to classify that particular user and recommendation process is restricted in terms of the features of suggested product (Burke, 2002). Additionally, in content-based technique, features for certain items such as movies, music and etc. are impossible with current technology to be identified. Knowledge-based recommender techniques do not have ramp-up problem and it does not need to classify particular user. Knowledge-based recommender technique also does not suffer from sparsity problem. Sparsity which is one of the major limitations for recommender techniques refers to the situation in which feedback data or ratings are sparse; that is, data is not sufficient to determine similarities in consumer tastes (Huang et al., 2004). However, knowledge-based recommender technique requires detailed knowledge about item domain, its features and etc. The solution to the problems mentioned above is to combine different recommender techniques into one in order to generate more precise recommendations by avoiding the drawbacks of the individual technique. For example, if knowledge about behavior, tastes and etc. of a large community of other users is known and if there is detailed information about the items, recommendation process can be enhanced by combining the collaborative filtering and content-based techniques (Jannach et al., 2011). In another approach, collaborative, content-based and demographic techniques are merged to overcome the cold start problem. Demographic recommender technique categorizes customers on the basis of personal attributes and generates suggestions accordingly. By using the demographic characteristics, new users are categorized into clusters and items are recommended based on the cluster that particular user belongs (Chikhaoui et al., 2011). There are different ways of combining collaborative and content-based recommender techniques. They can be implemented separately and their result can be combined together; characteristics of one technique can be incorporated into another one, or unifying model can be developed which incorporates characteristics of both techniques (Puntheeranurak & Tsuji, 2007).

2.2 Previous Studies on Recommender Systems

This section reviews the previous studies conducted in the field of recommender systems. Papers written on the issue analyze different aspects of recommender systems; however, studies that analyze the influence of RAs on consumer behavior can be generalized under one framework shown in Figure 5. This part of the review is about the influence of RAs on consumer behavior and consumer evaluation of these systems. Following subsections analyze the findings of the previous studies under the light of framework shown in Figure 5.

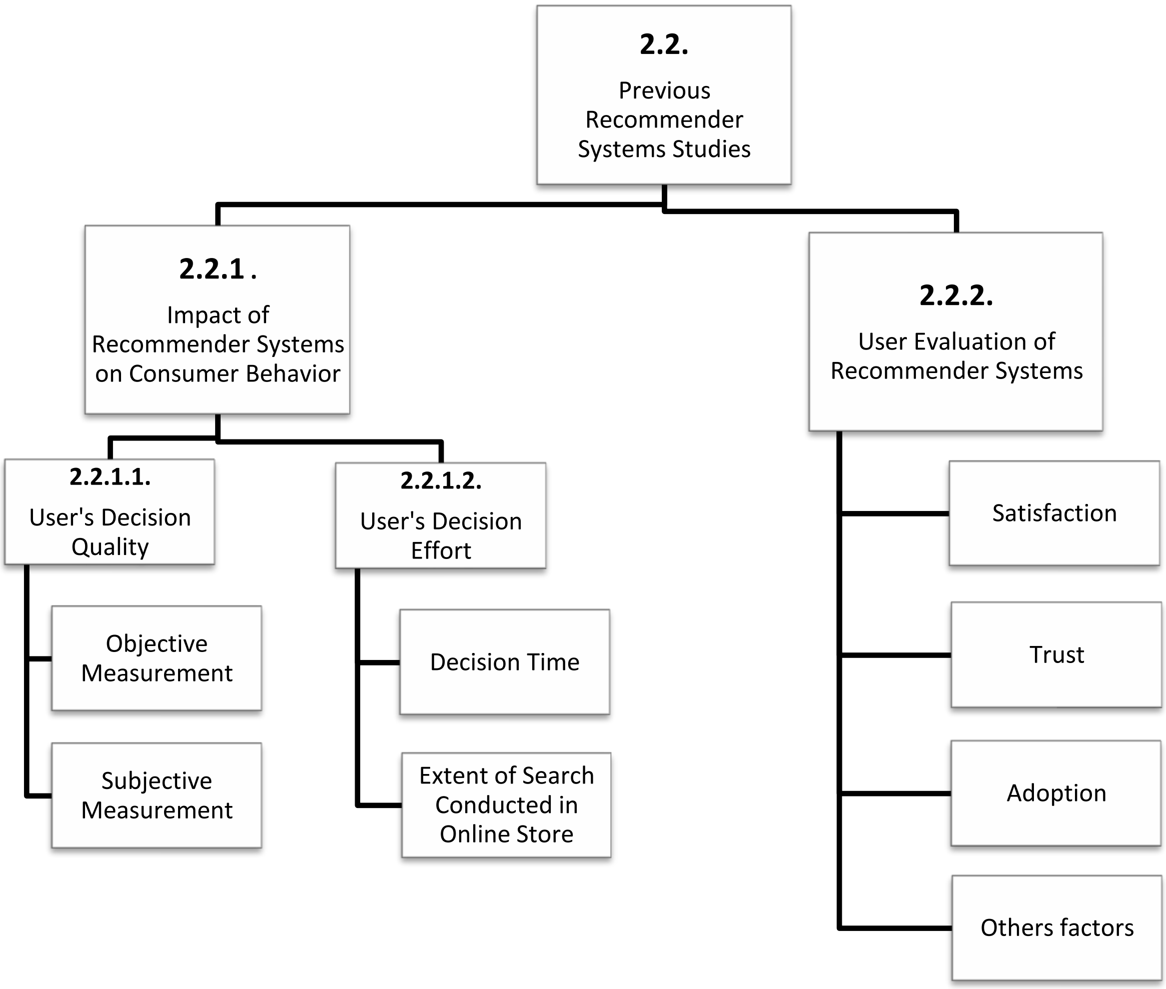

Figure 5 - Classification of Recommender System Studies

2.2.1 Impact of Recommender Systems on Consumer Behavior

RAs impact on consumer decision making process during online purchasing has been extensively researched in literature. In these studies, researchers analyzed the relation between the use of recommender systems and other main factors related to decision making process such as decision quality, decision effort, decision duration, extent of product search, product promotion effectiveness, and product search effectiveness. This sub-section reviews the existing literature related to recommender system impact on those factors mentioned above.

2.2.1.1 Decision Quality

One of the main factors that use of recommender system aims to influence is decision quality of online consumer. Decision quality at the end of the process refers to either objective or subjective quality of customers' purchasing decision (Xiao &Benbasat, 2007). There are several ways in the literature to measure the consumers' decision quality after being exposed to recommender systems. How closely consumer's choice from the set of alternatives matches to the ideal outcome is the most common way which is utilized to measure the decision quality (Hostler et al., 2005). Investigation of the RAs influence on decision quality of online customer has been studied in several researches. In their study Haubl & Trifts (2000) conducted one way of objective measurement of decision quality by examining whether customer purchased dominated or non-dominated product. A product is dominated if there is another alternative product whose at least one of the attributes is in higher quality. Non-dominated one is the product whose attributes are not lower in quality than the other products' and also at least one of the attributes is higher in quality than other products'. Study of Haubl & Trifts (2000) has statistical proofs which clearly show that the number of non-dominated products rises in the existence of RAs in the alternative set while the case of non-use of RAs increases the number of dominated items in the alternative set.

In their study Hostler et al. (2005) assigned score of "1" or "0" to each of the product features that user selected. Score "0" means that item feature is absent and score "1" means that particular feature is present. The aggregate score was used in calculation of the decision quality; that is, whether the product user selected has features specified in the experiment procedures or not. Their study showed that participants who have experienced shopping by the help of RA have proved to be better in purchasing decision than the participants who shopped without the aid of such a system.

The second approach that Haubl & Trifts (2000) used in order to measure decision quality of the online customer objectively is whether customers change their opinion and switches to another alternative if given a chance to do so. If customer switches to another product, this is assumed to be an indication of the poor decision quality. Result of the study carried out by them proved that the number of participants who switched to another product when given an opportunity was less in the existence of recommender system than absence of such a system. Olson & Widing (2002) also found the same results in their study as Haubl and Trifts (2000).

In another study by Haubl & Murray (2006), participants are asked to provide subjective preference information as an input for the recommendation systems' personalized preference model. Utility scores which estimate attractiveness of each product to the user have been calculated based on these inputs provided by the user and these scores have been used to calculate participants' decision quality. Scores have been standardized; that is, 0 refers to least attractive and 1 to the most attractive one. Their study result showed that use of recommender system increased consumer decision quality in terms of the attractiveness of the chosen product to the customer.

Results of the study conducted by Swaminathan (2003) statistically proved that use of such intelligent systems increases online consumers' decision quality when the perceived risk associated with the product is greater and when consumer has an in-depth knowledge about the product category s/he is about to purchase. Perceived risk in this context defined as consumers' perception of uncertainty and adverse consequence that may occur after purchasing the particular product and knowledge about the product category defined as consumer ability to distinguish between attributes of products.

In several studies, consumers' confidence in purchasing decision is considered as an indication of the subjective quality decision. Confidence in purchasing decision means the degree of customers' belief in the purchased items being the best option for them. Studies conducted showed that use of recommender system resulted in an increase in consumers' confidence in their purchasing decision (Olson & Widing 2002; Haubl & Trifts, 2000). However, several studies found contrary results. For example, Hostler et al. (2005) found no significant difference in decision confidence among subjects who used recommender system and who did not use such a system. Vijayasarathy& Jones (2001) found that from the two group of participants, the group who did not use recommender system as an aid for shopping task had more confidence in their decision than the group who did use recommender system.

2.2.1.2 Decision Effort

Impact of recommender systems on consumers' decision making effort is another important topic that has been analyzed by the researchers. According to Xiao and Benbasat (2007) consumer decision making effort in online environment can be measured by total duration required to come up with final decision and the broad of product search conducted. Decision duration can be defined as the necessary duration required for analyzing items' features and details, and come up with a final purchasing decision.

Extent or broad of product search refers to the number items that customer searched, gathered necessary information and considered for purchase.

In a simulated consumer banking situation, Pedersen (2000) showed that recommender assisted users to spend less time searching for information. Hostler et al. (2005) also tested whether or not recommender systems reduces time consumed by end users searching for and deciding on an item to purchase over online retailers' store. Time in that context included amount of time required to select a web store to shop on and time required to search and select a product on the selected store. His study exhibited statistically significant difference in decision duration between participant who assisted by recommender system and participant who did not assisted by such system. Study showed that use of recommender system increased users' performance by saving them time. Not all studies confirm these findings. For example, study result of Olson & Widing (2002) showed that recommender system assisted participants had longer actual and perceived decision time. They stated that this longer decision time probably occurred as a result of entering preference scores or weights to the system in order to get useful recommendations. The finding of the studies related to impact of recommender system on consumer decision making time is blurred; therefore, some further investigation is needed on this topic.

As mentioned above, another factor that defines online consumer decision making effort is the extent of product search. Researchers have conducted studies to analyze the relation between use of recommender system and extent of product search.

In general, consumers pass through two-stage process while making purchasing. Initially, they evaluate the available products and identify sub-set of products which are potential candidates for purchasing. Then, consumers evaluate the products in the sub-set in more detail by comparing the products' attributes and make purchasing decision (Haubl & Trifts, 2000). This two-stage process allows consumer to focus more on the products that meets their needs and make quality purchasing decisions. In a controlled experiment using simulated online store, Haubl & Trifts (2000) showed that participants who have been assisted by recommender system analyzed substantially fewer product details than the ones who haven't been assisted by such a system. Their study also showed participants who have been assisted by recommender system had smaller set of alternative products considered seriously for purchase.

2.2.2 User Evaluation of Recommender Systems

Users (customers) evaluation of RA is another area that researchers focus on. Satisfaction, loyalty, trust and acceptance and later use of RAs are among the factors that have been extensively researched in the literature as a primary factor of user evaluation.

Satisfaction has two elements which are "outcome satisfaction" and "process satisfaction" (Bechwati & Xia, 2003). Outcome satisfaction is derived from consuming the purchased product and process satisfaction comes from the search process conducted in the merchant's website. Process satisfaction is an important factor to be considered by online merchants if they want their customers continue using their services (Bechwati & Xia, 2003). In the literature, several papers have analyzed the customers' satisfaction with RAs and their decision making process which is facilitated by such systems. Bechwati & Xia (2003) conducted a study to see whether online consumers perceive work performed by recommender systems as an effort saving tool and whether this perception has any effect on their satisfaction with decision process. Their study result showed that perception of effort saved by RAs has positively affected the consumers' satisfaction level with decision making process. In other words, the more customers believe that such systems save effort, the more they become satisfied with the service. Another study showed that the use of RA led to increase in satisfaction level with both decision making process and interaction process (Felfering & Gula, 2006).

Customer’s satisfaction with the merchant’s website increases whenever s/he perceives the recommended items are helpful and useful (Hostler et al., 2012).Whether or not particular product is purchased by the customer is not a determining factor of customer satisfaction (Hostler et al., 2012). That is, s/he may find recommended item useful and may purchase item later for some reasons. In their study, Hostler et al. (2012) has found that product promotion effectiveness is a significant predictor of consumer satisfaction with retailers’ online stores. Product promotion effectiveness means ability of recommender system to recommend product, attract attention and develop interest in those particular items. Their study result has also showed that customer’s satisfaction level with web store is a significant predictor of customer’s loyalty to it; that is, consumer satisfaction with web store have positive effects on customers being loyal to it.

In an e-commerce environment trust is easy to lose and difficult to gain due to absence of face-to face interaction with consumer (Chen & Pu, 2005). Trust in recommender systems refers to the level to which online customers believe that intelligent agent advised them products which most closely fulfill their preferences (Pereira, 2000). In other words, trust in this context means customers beliefs in the recommender systems’ being competent, benevolent and consistent (Xiao & Benbasat, 2007). Competence is ability and skill to perform effectively on behalf of the consumer, benevolence is systems acting according to users best interests and consistent is the system’s being consistent with the set of principles that users find acceptable. Trust is an important factor in success of recommender systems. Recommender systems perform extensive task on behalf of customer and if customer do not trust such systems they will be reluctant to accept systems advice. In their study Wang & Benbasat (2005) statistically showed that customers’ initial trust in RAs has a direct influence on their being adopted for later use as well as their being perceived as a useful tool in online shopping. In their study Chen & Pu (2005) found that in order to achieve online consumers’ trust, recommender systems should give users explanations how it works, should explain how recommendations are generated and should organize the recommended items in such a way that it is easier to compare and contrast them. Another important factor is that users perceive recommender system easier to use if they allow users to generate new set of items without a lot of effort (Swearingen & Sinha, 2002).

In another study Pereira (2000) found that trust and satisfaction increases when degree of control given to user by means of ability to go back to preference input stage and change his or her preferences at any time, skip response to certain specification requested by system and giving an option to user to choose whichever product attributes s/he wants to exist in final product.

Correlation between trust in recommender systems and transparency of recommender systems was analyzed by Sinha & Swearingen (2001). Their study aimed to analyze the role of transparency in recommender systems; that's whether users' perception of why particular item is recommended has any effect in their trust in such systems. They stated that most of the recommender system acts like a black box and do not give insights to users about system logic or how recommendations are generated. Therefore, they hypothesized that users who do not have any idea about how recommended items are generated will have doubts in systems being trustworthy and will not take RAs suggestions into consideration. In order to test hypothesis they conducted a study which utilized music recommender system and result of their study supported their hypothesis. Users satisfied and feel more comfortable as a result of transparent recommender system than in non-transparent case.

CHAPTER III

RESEARCH MODEL AND HYPOTHESES

Proposed model of the study are explained in this section by considering previous models and papers written on the issue. This study aims to evaluate the influence of knowledge-based RAs on online consumer decision making process.

3.1 Conceptual Model of the Study

A proposed model is presented in Figure 6.

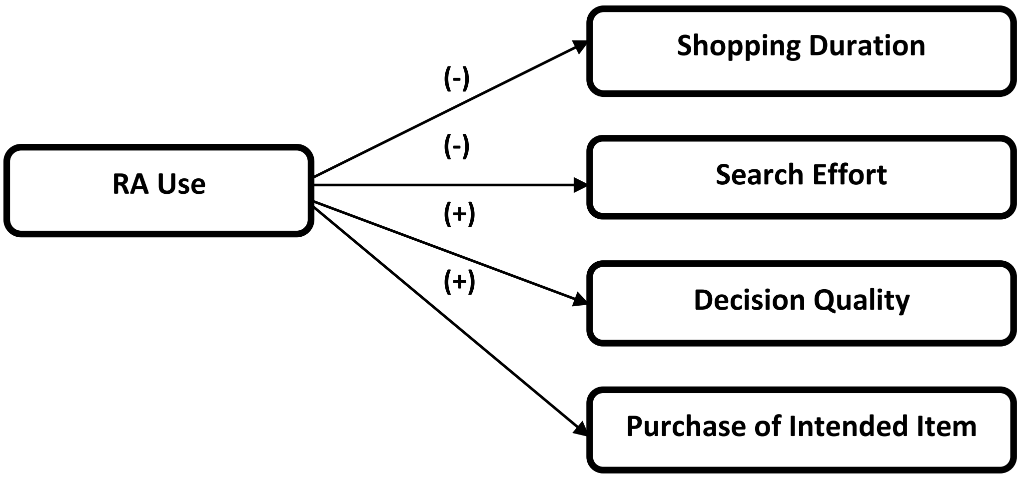

Figure 6 - Conceptual Model

3.1.1 Constructs of the Proposed Model

There exists four constructs in the conceptual model: shopping duration, search effort, decision quality and purchase of intended item. RA use is an independent variable in this study.

Shopping Duration and Search Effort

Time spent during shopping and effort spent in searching and analyzing products point to amount of total effort spent by the customer. Two factors which are used to measure this total effort are shopping time and extent or broad of product search (Xiao &Benbasat, 2007). In their studies, Pedersen (2000) and Hostler et al. (2005) have showed that user who are assisted by recommender systems have spent considerably less time in selecting product for purchasing than users who are not assisted by such systems. The extent of product search as a measure of effort has been analyzed by Haubl & Trifts (2000) and the result of their study showed that RA assisted users analyzed substantially fewer product details in simulated online store environment than the users who have not been assisted by such systems.

Therefore, the following hypotheses are put forward:

Hypothesis 1: There is negative relationship between the use of RA and shopping duration of user.

Hypothesis 2: There is negative relationship between the use of RA and search effort of user.

Decision Quality

Decision quality is a subjective or objective quality of consumers' purchase decision (Xiao &Benbasat, 2007). Researchers analyzed whether or not there exists any correlation between RA use and decision quality of online consumer by conducting both objective and subjective studies.

In the literature, subjective approach to measure decision quality was measured by considering the user's confidence level in purchasing decision. Olson & Widing (2002) and Haubl & Trifts (2000) showed that user who assisted by RA were more confident in their purchasing decision than non-RA case while Vijayasarathy & Jones (2001) found contrary results.

In the literature, objective approach to measure decision quality of online consumer consists of whether a user purchases dominated or non-dominated products among alternatives, obtaining the features that user wishes the final product to possess and calculating aggregate score of the final product by assigning score 1 (feature exists) or 0 (does not exist), giving a chance to a user to change the final product he or she is about to purchase with another product, and obtaining preference information from the user to calculate attractiveness of final product to that specific user. Study results of Haubl & Trifts (2000) showed that recommender systems increase quality of consumers' decision by raising the total number of non-dominated products in the alternative set which customers seriously considers for purchasing. In addition, Haubl & Trifts (2000) and Olson & Widing (2002) showed that the number of users who changed his or her mind and purchased another product when given a chance was less in the existence of RA than absence of RA. Hostler et al. (2005) also indicated that RA assisted users made better overall decision than non-RA users. Another research showed that RA use increased decision quality of the user in terms of the attractiveness of the chosen product to that user Haubl & Murray (2006).

Based on the discussion above it is proposed that:

Hypothesis 3: Use of RA is positively related to decision quality of user.

Purchase of Intended Item

Information overload causes consumers to mistakenly purchase items that do not match to their preferences or they have never intended to buy. In that respect, recommender agents improve customers' decision making process by reducing information load and search complexity. In the meanwhile, recommender agents increase consumer decision quality by recommending products and services which customer is interested in and intended to purchase (Hanani et al., 2001;Chiasson et al., 2002).

In this study, purchase of intended item by participants refers to the case that whether participant purchase a product that possess properties which customer specified before starting the simulated shopping task. It is expected that use of recommender agents will led participants to purchase a product which possesses properties that participants wanted to exist. Purchase of intended item by consumer can be considered as another measure of overall decision quality of online consumer.

Therefore, it is proposed that:

Hypothesis 4: Use of RA is positively related to purchase of intended item by user.

CHAPTER IV

RESEARCH METHODOLOGY

Research methodology of this study is explained in this chapter. Initially, study setting, experimental design, experimental shopping agent and data collection of the study are clarified. Later, ethical clearance and sample selection are given. Data analysis of the study is explained at the final part. Structure of the methodology is given in Figure 7.

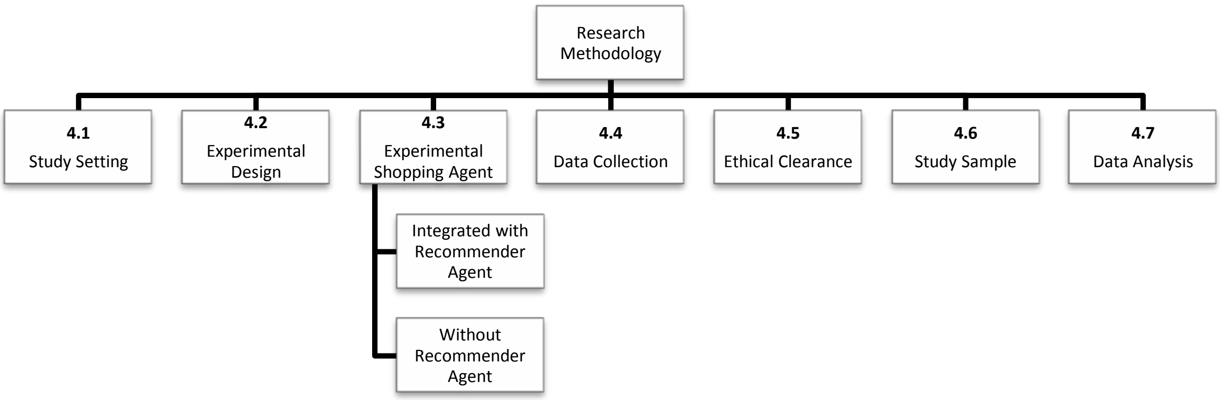

Figure 7 - Structure of Research Methodology

4.1 Study Setting

This study has been carried out at Middle East Technical University (METU) in Ankara, Turkey. Study participants were graduate and undergraduate students from various faculties of METU. All participants were computer literate and had experience or understanding of online shopping. Since the language of instruction at METU is English, research was prepared and conducted in English.

4.2 Experimental Design

This study makes use of between-subjects experimental design to analyze the influence of RAs on consumer behavior. In order to test the developed conceptual model, data has been collected through simulated online shopping experiment. Two online shopping systems have been developed by using ASP.NET framework which is a web application framework developed, maintained and marketed by Microsoft Corporation. One of the developed systems has been integrated with knowledge-based recommender system and the other system simply has utilized basic filtering system.

Students were invited by email to participate in survey. Students who accepted to participate were randomly sent the URL of one of the systems. The treatment group has used recommender system, while the control group has used simple filtering system. In the simulated shopping task subjects are required to purchase a digital camera. Before starting to the experiment purpose of the study and instructions on how to use simulated store have been explained to the subjects. In addition, they have been told to consider as if they have average income while purchasing a digital camera and they have been instructed to purchase only one digital camera that meets their requirements.

Two different data sets have been collected during the survey. Appendix G and H shows pretest survey items and record sheet for these data sets. The first data set are shopping system log data which are collected and saved to database by shopping system. Appendix F shows the log record sheet for both RA and NRA shopping systems. This data set is consisted of shopping duration, search effort, and decision quality and purchase of intended item by online consumer. The second data set are demographic and technological background details. Before starting the survey subjects have been instructed to input a nickname to the system and they have been required to specify the same nickname in the questionnaire so that two different data sets can be linked.

4.3 Experimental Shopping Agent

As it is mentioned before two online stores have been developed and one of these stores has been integrated with knowledge-based recommender system while the other one is not integrated with such system.

4.3.1 Shopping System with Recommender Agent

This section explains the internal structure of the shopping system which is integrated by recommender system. This shopping system welcomes user with the screen given at Figure 8. Firstly, subjects are required to get familiar with photography types by following the instructions given on the welcome screen. Then subjects were instructed to enter their nickname and photography category in which they are interested. That is, they should choose the photography type of digital camera they intend to purchase by using this system. Both RA and NRA have used the same welcome screen.

Figure 8 - Recommender System (Welcome Screen)

Figure 9 shows the steps required to be followed by subjects using RA integrated shopping system. System asks participants just seven questions in the following categories: price, usage, photography, condition, pricing, memory and battery.

Based on the answers obtained from the participants, system searches across 649 digital cameras which are stored in the product database and brings the most suitable ones to the participants. Those cameras are divided into five categories based on their technical specifications as landscape, portrait, macro, sports and extreme sports. Technical specifications of those 649 cameras are determined based on the camera specifications of the famous brands such as Canon, Nikon and etc. The same camera database was used for both RA and NRA integrated shopping systems.

Subjects can easily navigate to any question at any stage of the purchasing process and re-specify their selections by simply clicking the images shown in Figure 9.

Figure 9 - Recommender System (Shopping Steps)

When compared with other RAs, knowledge-based recommender systems are highly interactive. Such systems require strong interaction between user and the system. It is also different from simple filtering systems which we can see in most online shopping stores. Simple filtering systems just focus on item specifications and they do not consider whether users have any knowledge or experience with product domain. As it is shown in Figure 10, rather than asking participants which technical details s/he wants camera to possess, system collects user requirements by asking easily comprehensible questions. Based on the answers given to the questions RA generates recommendations with specifications that meet user requirements. As it shown in Figure 10, in case users want to get more information about meanings of technical specifications terms, they can navigate to the "Glossary" link at the top of the shopping window. In addition, participants have an option to examine all available cameras by simply clicking on the "All Cameras" link at the top of the same shopping window.

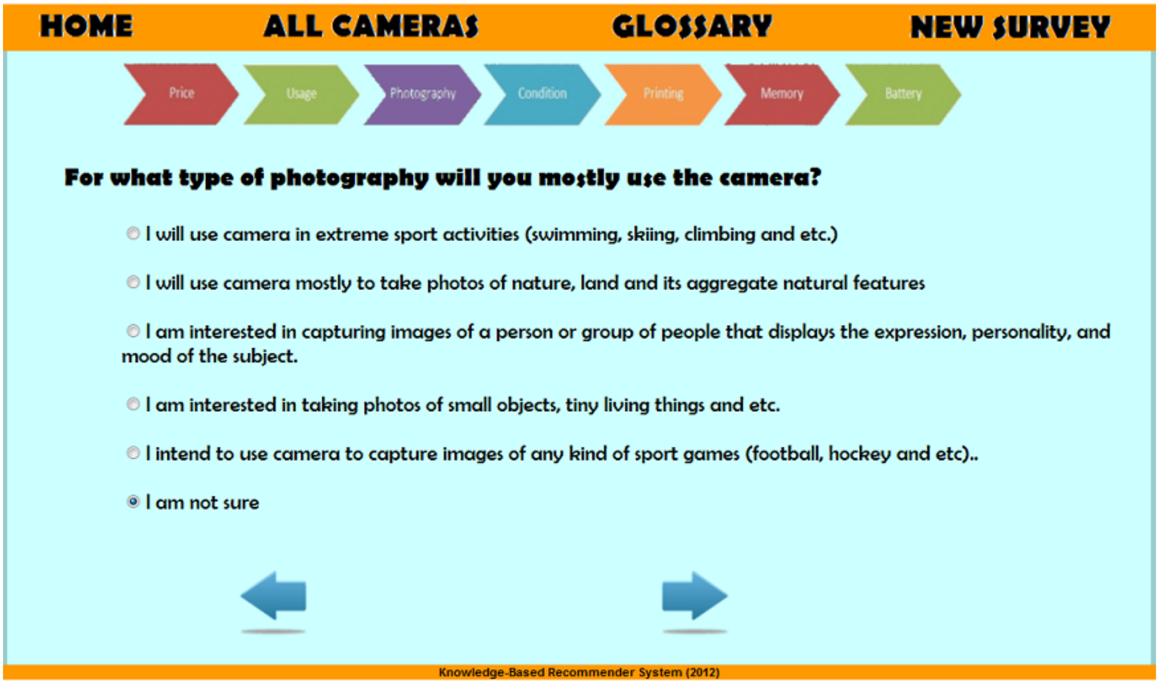

Figure 10 - Recommender System (Photography Step)

When compared with other RAs, knowledge-based system requires in-depth product domain knowledge and it needs to be engineered and organized in such a way that it can be easily retrieved (Chun & Hong, 2001).

As it shown in Figure 11, when participant makes a selection to one of the category questions which conflicts with another selection of another category, s/he prompted about the conflict and necessary explanations are given to the user how to make corrections. After the necessary corrections are made recommended products are presented to the user.

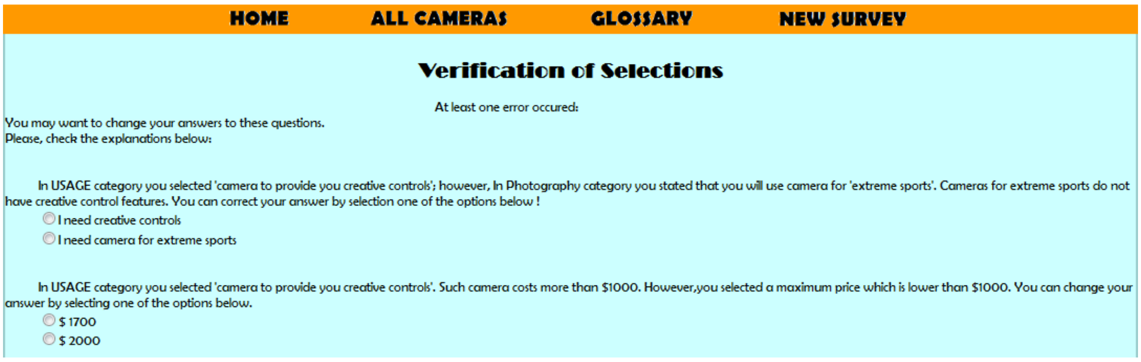

Figure 11 - Recommender System (Verification of Selections)

Figure 12 shows the interface that user sees when s/he proceeds to purchase a camera among alternatives recommended by RA. This page lists product specification and detailed explanation why this specific camera is recommended to the user.

Figure 12 - Recommender System (Purchase Item)

There are two types of knowledge-based RAs which are constraint-based and case-based. In this research, developed RA is constraint-based and it generates recommendations according to explicitly set rules. As it is mentioned in "Recommender Systems: An Introduction" book by Jannach et al. (2011) constrained-based system can be represented as a *constraint satisfaction problem (CSP)* and can be solved by a constraint solver or in the form of conjunctive queries. Table 2 below shows the example recommendation task.

Table 2 - Example Recommendation Task

V_c	*{Max-Price (200...2000), Usage (Simple, Advanced), Photography (Extreme, Landscape, Portrait, Macro, Sports), Printing (Digital, Small-Print, Large-Print), Memory (Small, Moderate, Large), Etc.}*
V_{PROD}	*{ Price (100...2000), Megapixel(3...18), Optical-Zoom(3...21), Lcd-Size(2...4), Battery-Type (Lithium, Alkaline), Focal-Length(15...480), Closest-Focus(0...6), Max-Aperture (1...6), Waterproof(Yes, No), Shockproof(Yes, No), Etc.}*
C_R	*{ Usage=Advanced → Price>1000, Photography=Extreme → Price>400, Usage=Advanced → Photography ≠ Extreme, Photography =Extreme →Battery ≠ Regular, Etc.}*
C_F	*{ Usage=Simple → Type=Digital Compact, Usage=Advanced →Type=Digital SLR, Printing=Large → Mega Pixel>=10, Printing=Small → Mega Pixel=[6-10], Photography=Extreme → Waterproof=Yes, Photography=Macro → Closest Focus= [0.20mm...0.31mm], Photography=Macro → Focal Length= [50mm...180mm], Photography=Sports → Closest Focus= [2.70mm...6.00mm], Photography=Sports → Focal Length= [120mm...480mm], Etc.}*
C_{PROD}	*{(Type=Digital Compact ∧Price=130 ∧Mega-Pixel=4 ∧ Optical-Zoom=2 ∧ Waterproof=No ∧ Shockproof=No ∧ Closest-Focus=0.35 ∧Max-ISO=800 ∧ Max-Aperture=2.4 ∧ Magnification=0.20 ∧ Memory=1 ∧ Battery=Lithium)∨(....)∨ (....)}*
REQ	*{Max-Price=200, Usage=Simple, Condition=Low Light, Photography=Portrait, Printing=Digital, Memory=Small, Battery=Regular}*
RES	*{ (Type=Digital Compact | Price=122 | Mega-Pixel=4 | Optical-Zoom=2 | Waterproof=No | Shockproof=No | Closest-Focus=0.35 | Max-ISO=800 | Max-Aperture=2.4 | Magnification=0.20 | Memory=1 | Battery=Alkaline)}*

***All these specifications in the table have been determined based on camera specifications of famous brands such as Canon, Nikon and etc.*

While users are interacting with RA integrated website, system tracks shopping duration, number of page views, purchased item and decision quality of each user and saves these data to the database. Purchased item by the customer is used to determine whether the final purchased item matches to initially intended item by the customer. If the final selection matches it will be saved “Yes” and if not it will be saved as “No”. Decision quality is assessed by giving a chance to the participant to change his or her final selection and switch a product which belongs to completely different category at the end of the shopping task. If s/he changes his or her selection this is saved to the database as “Yes” and if decision is not changed it is saved as “No” to the database. “Yes” shows poor decision quality while “No” represents strong decision quality. This is one of the objective approaches to measure decision quality which has been used in RA literature.

4.3.2 Shopping System without Recommender Agent

The second shopping system is not integrated with recommender system. Interface and functionality of this system is similar to most shopping systems which we can encounter on the web. In NRA shopping system user simply selects camera by using camera filtering functionality. By using camera filtering functionality, user inputs technical details which s/he wants camera to possess. Then, shopping system searches across product database and retrieves products based on user inputs. Then, user can sort the retrieved results with camera sorting functionality. For example, in RA integrated system, users input to the system that they need a camera for large print purposes and knowledge-based recommender system searches across product database for digital cameras which meet the requirement of large printing. However, in NRA shopping system users themselves need to know the product requirements for large printing and need to select that requirement from the given options. Such shopping systems assume that users have product domain knowledge and users are expected to purchase appropriate products by using product filtering functionality. Not all consumers have in-depth product domain knowledge; therefore, consumers who utilize simple filtering systems sometimes end up with wrong product selections. By using such systems, users sometimes focus on product specifications which are not actually meet their demand but those features seem important to the customer and they decide on which product they will buy according to those features by neglecting their needs. In this way, customers sometimes end up with a product which actually does not meet their needs.

Figure 13 shows the user interface of this shopping system. In this study, NRA shopping system utilizes the same product database with RA integrated system; that is, participants of NRA shopping system search suitable cameras among 649 available items. As in RA case, those cameras are divided into 5 categories based on their different specifications. Those categories are landscape, portrait, macro, sports and extreme sports. In order to choose the correct camera for their needs, participants are required to know technical specifications of the given category and by using the filtering system they are required to find and purchase the camera which is thought to be suitable for their needs. During the shopping session, participants can always refer to glossary section in order to get more information about the product specifications.

As in the RA integrated system, this system also tracks shopping duration, number of page views, purchased item and decision quality of each user and saves these data to the database.

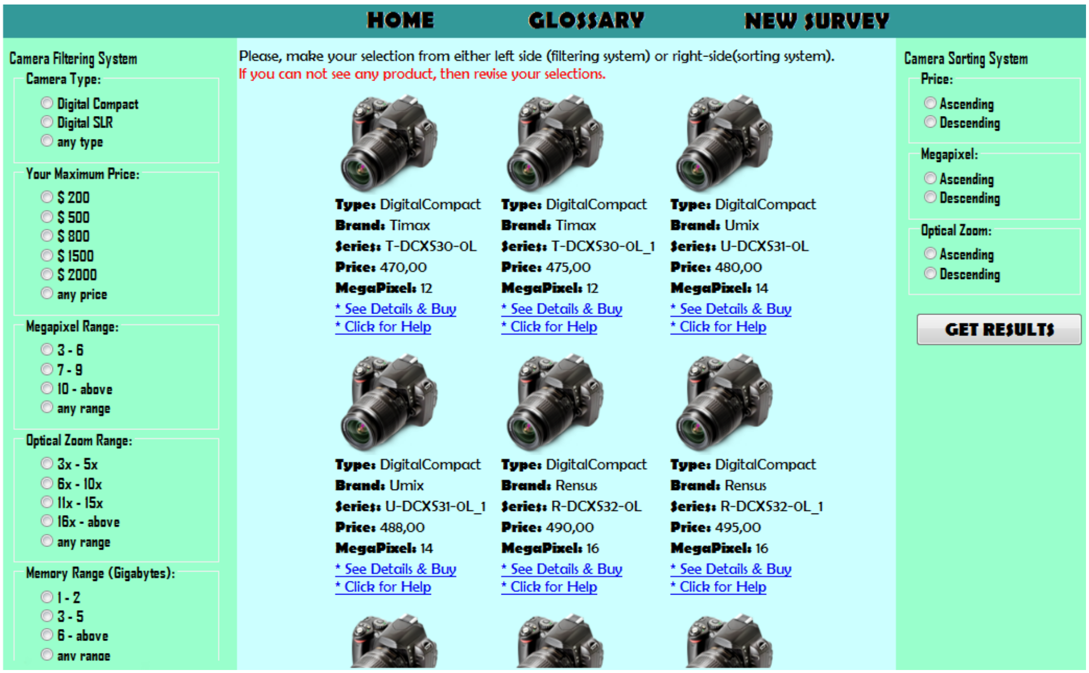

Figure 13 - Non-Recommender System

4.4 Data Collection

Necessary data for this research was gathered at Middle East Technical University. Students were invited to participate in the survey via email. Participants who replied with an intention to participate in the survey were sent the URL of the shopping website along with an online survey questionnaire. Questionnaire sent to participants was prepared by using online survey tools. In total 223 survey results were collected from volunteers in 1 month period. Participants of the survey were graduate and undergraduate students from various faculties.

4.5 Ethical Clearance

It is required to take permission from "Research Center for Applied Ethics" at METU before conducting the survey with human participants. The survey of this research was approved by Research Center for Applied Ethics (Appendix F).

4.6 Study Sample

Sampling is the process of choosing units from a population of interest. By studying the sample we can conclude results back to the population from which the sample is chosen. Since data are collected randomly without using any algorithm and participants are chosen according to ease of access, the sampling method of this study is non-probability sampling. Two independent samples which are used in this study are pilot and main study samples.

Pilot study sample: This sample consists of 30 participants at METU. Pilot study is conducted to check that the survey instructions are comprehensible, wording of the survey is correct, results are reliable and valid, and statistical processes are effective. Necessary modifications are made to survey questions and experiment procedure instructions based on the feedbacks received from the pilot group.

Main study Sample: This sample is consisted of 223 students. 115 of them are assigned to treatment group and 108 to control group. All participants are graduate and undergraduate students of METU.

4.7 Data Analyses

In this study, parametric and non-parametric statistical tools are utilized to test the study hypotheses. As the measurement scale of two dependent variables follow continuous data pattern, parametric "Independent-samples t-test" is employed. Chi-square test is used for the other dependent variables since they have nominal measurement scale. Parametric statistical tests require sample data to follow some type of probability distribution such as normal distribution. However, non-parametric statistical tests are often called non-distribution tests because they do not make any assumptions about the distribution of data.

This study aims to measure several dependent variables in two independent groups (recommender agent / non-recommender agent users) in order to see if there exist any mean differences in the dependent variables.

Independent-samples t-test is employed in order to explore mean differences on a continuous dependent variable between two groups of an independent variable. The reason of conducting the t-test is to explore whether the population means of the study groups are different and this difference is not occurred due to natural sampling variation. In other words, it is used to compare whether the average difference between two groups is statistically significant or not.

In order to conduct independent sample t-test following conditions must be met:

- One categorical independent variable with two groups. Participants in each group are different; that's, one participant cannot be present at more than one group at the same time.
- At least one continuous dependent variable.

In order to get valid results from independent-samples t-test following assumptions must be met:

- Independence of observations
- No outliers
- Normality
- Homogeneity of variances

As it mentioned before, independent-samples t-test requires that there must be different participants in each group with no participant in more than one group. It is important that independence of observations not violated in order to get valid results. Since outliers usually have negative impact on the results by influencing the group mean it is important to handle them properly. In addition to outliers, independent-samples t-test requires that the dependent variables to be normally distributed. In data analysis chapter, trimmed mean results are used to identify outliers and Kolmogorov-Smirnov Test for Normality is used to determine whether data is normally distributed. Homogeneity of variances assumes that the population variance for each group is the same. Levene's Test for Equal Variances is used to test homogeneity of variances assumption.

Another statistical test used in this research is Chi-square test for the difference between independent samples. Two of the dependent constructs (Decision quality, Purchase of Intended Item) in this study are categorical (nominal) data. In statistics, chi-square is used to explore mean differences on a nominal dependent variable between two groups of an independent variable. Whether the distributions of categorical variables differ from each other can be determined by utilizing a chi-square test.

A non-parametric Mann-Whitney U Test is the third statistical tool which is used in this study. This test is generally used to determine mean differences on an ordinal dependent variable between two groups of an independent variable. In this study, a Mann-Whitney U Test is used to assess differences between the RA and non-RA user groups in eight pretest items.

CHAPTER V

DATA ANALYSIS

Statistical analyses of this research are given in this chapter. SPSS Statistics 17 is used in conducting all necessary statistics.

5.1 Preliminary Analysis

This part of the chapter is about descriptive statistics of collected dataset. In this section, demographic frequencies, missing data, outliers, distribution of data and homogeneity test between groups are given respectively.

5.1.1 Demographic frequencies

The study sample was composed of 223 undergraduate and graduate students from various faculties of METU. Frequency statistics of male and female students are given in Table 3. There are 126 male and 97 female students.

Table 3 - Gender frequencies (Overall)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	97	43.5	43.5	43.5
	M	126	56.5	56.5	100.0
	Total	223	100.0	100.0	

In the study there are control and treatment groups. There are 115 students in treatment group (RA) and 108 students in control group (NRA). Gender frequencies of control and treatment groups are given in Table 4 and 5.

Table 4 - Within group gender frequencies (RA)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	54	47.0	47.0	47.0
	M	61	53.0	53.0	100.0
	Total	115	100.0	100.0	

Table 5 - Within group gender frequencies (NRA)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	43	39.8	39.8	39.8
	M	65	60.2	60.2	100.0
	Total	108	100.0	100.0	

Age frequencies of RA and Non-RA user groups are given in Table 6. In RA sample frequency of age 22 is the greatest with a percentage 31.30. However, in NRA sample frequency of age 23 is the greatest one with a percentage 22.22. From the final column of Table 6 most of the participants are at the age of 22 (% 24.21).

Table 6 - Age Frequencies

Age	RA (Frequency)	RA (%)	NRA (Frequency)	NRA (%)	Total (Frequency)	Total (%)
17	-	-	1	0.92	1	**0.44**
18	3	2.60	1	0.92	4	**1.79**
19	1	0.86	1	0.92	2	**0.89**
20	6	5.21	9	8.33	15	**6.72**
21	11	9.56	15	13.88	26	**11.65**
22	36	31.30	18	16.66	54	**24.21**
23	15	13.04	24	22.22	39	**17.48**
24	20	17.39	18	16.66	38	**17.04**
25	15	13.04	13	12.03	28	**12.55**
26	4	3.47	8	7.40	12	**5.38**
27	3	2.60	-	-	3	**1.34**
28	1	0.86	-	-	1	**0.44**
Total	**115**	**100%**	**108**	**100%**	**223**	**100%**

5.1.2 Checking for the missing data

In statistics, missing data or missing value occurs when participants fail or skip giving response to the given questionnaire items. It is important to identify missing data and handle them properly in order to get valid results.

In this study developed shopping systems tracked participants' actions during the simulated shopping session and logged and saved the necessary data to the database. That's, dataset of this study obtained by using objective methods rather than subjective methods. Therefore, missing data due to participants are not applicable to this study.

5.1.3 Outlier detection

Outlier refers to the observation that numerically stands distant from other observations in dataset. In other words, an outlier is an observation in a given sample which seems to deviate significantly from other observations of the same sample. There are several methods to detect and analyze outliers in the dataset. Trimmed means is one of the several methods to detect and analyze the outliers in a given sample. Trimmed mean or truncated mean is a family of measures of central tendency. In order to decrease the impact of outliers on the calculated mean, it calculates the mean after discarding the given parts of sample at the high and low end. Appendix A shows the mean and %5 trimmed mean of *duration* and *number of page search* factors. Results of trimmed mean statistics revealed no extreme differences between mean and trimmed mean for those factors.

5.1.4 Distribution of data: Normality

In contrast to non-parametric tests, parametric tests require data to be normally distributed. Normality tests are utilized to see whether a data set is well-modeled by a normal distribution. Standard normal distribution refers to the case where $\mu = 0$ (mean) and $\sigma = 1$ (standard deviation). A data set is accepted to be normally distributed if the data resembles a symmetric bell-shaped curve (Huck, 2004). In order to check normality of the given data set several graphical and statistical methods can be used. Histograms, Q-Q plots and box plot can be used to graphically determine normality of the dataset. In addition to graphical tests, Kolmogorov-Smirnov, Anderson-Darling and Shapiro-Wilk tests can be used to statistically check whether dataset follows normal distribution. Statistical test for normality are assumed to be more accurate because actual probabilities are calculated. The Shapiro-Wilk test is used if the sample size is small (<50 participants) and Kolmogorov-Smirnov test is used if the sample size is large.

In this study, Kolmogorov-Smirnov test is utilized to check the normality of the dataset because the sample size is large (>50 participants). SPSS Statistics 17 is used in order to conduct statistical tests which are mentioned above. Outputs of the Kolmogorov-Smirnov test are given in Table 7 and Table 8. In Kolmogorov-Smirnov test, if value in *sig* column is greater than *0.05* it can be concluded that data comes from normal distribution otherwise data cannot be considered to follow normal distribution. In Table 7 and 8 sig values are greater than *0.05* for both shopping duration and search effort items.

Table 7 - Tests of Normality (Duration)

	Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Shopping Duration	NRA	.059	108	.200*	.985	108	.260
	RA	.053	115	.200*	.983	115	.144

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.

Table 8 - Test of Normality (Search Effort)

	Type	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Search Effort	NRA	.079	108	.093	.984	108	.216
	RA	.080	115	.070	.978	115	.056

a. Lilliefors Significance Correction

5.1.5 Homogeneity test between groups

As it mentioned before there are two groups in this study, namely; control and treatment groups. Treatment group are exposed to knowledge-based recommender system while the control group used simple filtering system during the simulated shopping session. In order to see differences between RA user group (control) and non-RA user group (treatment) on various areas, participants have been required to fill 8 pretest items before starting the simulated shopping session. These pretest 8 pretest items included questions related to participants' computer usage level, internet usage level, frequency of visiting shopping websites, frequency of purchasing product from internet, knowledge level of camera technology, frequency of using camera and etc. Non-parametric Mann-Whitney U is used to test the possible difference that might exist between groups.

Before running the Mann-Whitney following conditions to be met:

- One independent variable which is dichotomous (e.g., RA / NRA)
- At least one dependent variable which is ordinal
- Independence between selected samples
- Equality of variances between groups

All of the required conditions are met before running the required tests. Appendix B shows the non-parametric Levene's test result of equal variances. Since the Sig. value is greater than 0.05 in all pretest items we can conclude that variances of two samples are statistically equal.

SPSS Statistics 17 is used to conduct the Mann-Whitney U test. Summary of the test results are given in Table 9. Appendix C and D lists the mean rank and result of the Mann-Whitney U test respectively. Since the pretest items' p values (Asymptotic Sig.) which have been derived from Mann-Whitney U test are greater than 0.05, it can be said that no statistically significant difference exists between scores of control and treatment group for 8 pretest items which are related to computer usage, internet usage, shopping experience and camera experience.

Table 9 - Mann-Whitney U Test Result

Pretest Item	Asymp. Sig. (2-tailed)
Computer Experience	.770
Frequency of Computer Usage	.644
Frequency of Internet Usage	.192
Frequency of Visiting Shopping Websites	.372
Frequency of Purchasing Product Online	.886
Knowledge Level of Camera Technology	.991
Camera Usage Experience	.900
Camera Usage Frequency	.933

5.2 Hypotheses Testing

5.2.1 Independent-Samples T-Test analysis

Group statistics of "Shopping Duration" dependent variable are given at Table 10. Each row in the table presents several statistics on the dependent variable, shopping duration, for the different categories of the independent variable, namely; RA and NRA. There are 115 participant at RA (treatment) group and 108 participants at NRA (control) group. Mean score of the treatment group is 189.64 while this figure is 278.75 for the control group. In other words, participants in treatment group spent less time in simulated shopping task than participants in control group. Another statistical figure given in Table 10 is the standard deviation of the shopping duration. Standard deviation of treatment group is 41.151 while this figure is 49.643 for the control group. Based on the figures given at Table 10 it can be summarized that mean control group shopping duration (278.75 ± 49.643) was higher than mean treatment group shopping duration (189.64 ± 41.151).

Table 10 - Group Statistics (Shopping Duration)

	Type	N	Mean	Std. Deviation	Std. Error Mean
Shopping Duration	RA	115	189.64	41.151	3.837
	NRA	108	278.75	49.643	4.777

Now that the overall impression of the data from the group statistics are derived from Table 10, it is required to determine the size (magnitude) of the difference between the two groups and to determine whether if this mean difference is statistically significant or not.

As it mentioned before homogeneity of variances is one of the assumptions of independent samples t-test. Table 11 shows both Levene's test for equality of variances and t-test for equality of means figures. It is important to determine whether equal variances assumption is met or not violated since it affects how t-test is calculated and its results reported. It is also important to make necessary calculation and interpretations if homogeneity of variances are not met otherwise this can affect the Type I error rate.

In order to check equality of variances it is required to check "Sig." column which is located under the "Levine's Test for Equality of Variances" column. If the population variances of treatment group and control group are equal, this test will return a p-value greater than 0.05 ($p>0.05$), indicating that the assumption of homogeneity of variances is met. If this figure is less than 0.05 ($p<0.05$), it indicates that equality of variances assumption is violated. When Table 11 is checked, it can be seen that "sig." Column under Levine's test generated p value which is 0.088($p=0.088$). Since this value is greater than 0.05, it can be concluded that the population variances of the shopping duration for both groups are equal; that's, the assumption of homogeneity of variances is met.

As the assumption of equal variances is met, the row which is labeled as "Equal Variances Assumed" needs to be interpreted. After checking the variances, it is worth to establish and report the mean difference between control and treatment groups along with likely range of the mean difference. It can be seen from the Table 11 below that the mean difference in shopping duration between control and treatment group is -89.107, the standard error of the mean difference is 6.092, and the 95% confidence intervals are from -101.112 and -77.101. This figures indicates that the mean difference in shopping duration score was -89.107 and that we can be 95% sure that the true mean difference lies somewhere between -101.112 and -77.101. In other words, treatment group mean shopping duration score was -89.107

(95% CI, -101.112 to -89.107) lower than control group mean shopping duration score.

So far necessary information on the magnitude of the difference is presented and explained. It is also important to analyze whether the mean difference (shopping duration) which explained before is statistically significant. In order to test whether the mean difference is statistically significant, it is required to check the middle portion of the Independent Samples Test which is generated by SPSS. If the "Sig. (2-tailed)" value is less than 0.05 ($p<0.05$), this means that the mean difference between two groups is statistically significant. However, if "Sig." Value is greater than 0.05 ($p>0.05$), there is no statistically significant mean difference between control and treatment groups. In Table 11, "Sig. (2-tailed)" value is less than 0.05 (i.e. $p<0.05$). Therefore, it can be concluded that recommender agent users and non-recommender agent users have statistically significantly different mean shopping duration. In other words, the mean difference in shopping duration between control and treatment is statistically significant. This statistical fact also supports the hypothesis 1 which states that *"Use of RA is negatively related to shopping duration of user."*

Table 11 - Independent Samples Test (Shopping Duration)

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Shopping Duration	Equal variances assumed	2.938	.088	-14.628	221	.000	-89.107	6.092	-101.112	-77.101
	Equal variances not assumed			-14.542	208.256	.000	-89.107	6.127	-101.186	-77.027

Group statistics of “Search Effort” dependent variable are given at Table 12. Mean score of the treatment group is 16.10 while this figure is 24.89 for the control group. Participants in treatment group searched less pages in simulated shopping task than participants in control group. Standard deviation of treatment group is 3.399 while this figure is 6.388 for the control group. Based on the figures given at Table 12 it can be concluded that mean control group shopping effort (24.89 ± 6.388) was higher than mean treatment group shopping duration (16.10 ± 3.399).

Table 12 - Group Statistics (Search Effort)

	Type	N	Mean	Std. Deviation	Std. Error Mean
Search Effort	RA	115	16.10	3.399	.317
	NRA	108	24.89	6.388	.615

Table 13 shows Levene's test for equality of variances and t-test for equality of means figures for dependent variable search effort. "Sig." value in Table 13 is less than 0.05 (i.e. $p<0.05$) which indicates that variances of control and treatment groups are unequal and the assumption of homogeneity of variances has been violated. As the assumption of equal variances has not been met, the row which is labeled as "*Equal Variances not Assumed*" needs to be interpreted. This row attempts to correct the unequal variances by utilizing the Welch-Satterthwaite degrees of freedom correction and non-pooled variances calculation of the t-statistics.

It can be seen from the Table 13 that the mean difference in search effort between control and treatment group is *-8.785*, the standard error of the mean difference is *0.692*, and the *95%* confidence intervals are from -10.150 and -7.419. These figures indicate that the mean difference in search effort was -8.785 and that we can be 95% sure that the true mean difference lies somewhere between -10.150 and -7.419. In other words, treatment group mean search effort was *-8.785 (95% CI, -10.150* to *-7.419)* lower than control group mean search effort.

In order to test whether this mean difference is statistically significant, it is required to check the middle portion of the Independent Samples Test. In Table 13, "Sig. (2-tailed)" value is less than 0.05 (i.e. $p<0.05$). Therefore, it can be concluded that control and treatment groups have statistically significantly different mean shopping effort. That is, the mean difference in shopping duration between control and treatment is statistically significant. These results support the hypothesis 2 which states that *"Use of RA is negatively related to search effort of user"*. This implies that recommender agent users are more likely to exert less effort and search across fewer pages than non-RA users.

Table 13 - Independent Samples Test (Search Effort)

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Search Effort	Equal variances assumed	32.709	.000	-12.928	221	.000	-8.785	.680	-10.124	-7.445
	Equal variances not assumed			-12.702	160.779	.000	-8.785	.692	-10.150	-7.419

5.2.2 Chi-Square for Difference analysis

A chi square (X^2) statistic for difference is used to investigate whether distributions of categorical variables differ from one another. In other words, it compares the counts of categorical responses between two (or more) independent groups. Since measures of dependent variables decision quality and purchase of intended item are categorical (nominal) data, a chi square (X^2) test is used to determine whether there exists statistically significant difference between the responses obtained from control and treatment groups. Bar chart which is given in Figure 14 shows that in treatment group 71 (61.74%) out of 115 participants did not switch to another product at the final stage of shopping task when given an opportunity.

However, in control group 48 (44.44%) out of 108 participants did not change the product they selected to purchase with another product when given an opportunity to do so. Appendix E shows the cross tabulation figures of the dependent variable *decision quality*. A chi square test will assess whether this difference between control and treatment group is statistically significant.

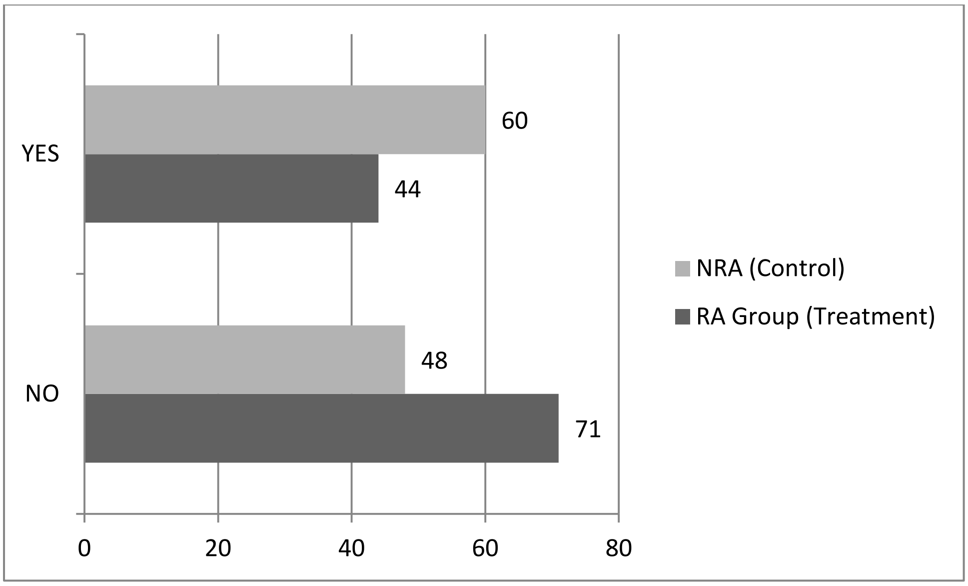

Figure 14 - Decision Quality of Control and Treatment Groups

Table 14 shows that chi square statistic (x^2=6.694), degree of freedom (df=1) and asymptotic significance (p=0.010). Since "Asymp.Sig." value (p=0.010) is less than the predetermined alpha level of significance (p=0.05), it can be concluded the difference between control and treatment group is statistically significant. This result supports the hypothesis 3 which states that "*Use of RA is positively related to decision quality of user*". These results imply that recommender agent users are less likely to change the item which they have selected with assistance of RA with randomly offered item.

Table 14 - Chi-Square Tests (Decision Quality)

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	6.694[a]	1	.010		
Continuity Correction[b]	6.017	1	.014		
Likelihood Ratio	6.725	1	.010		
Fisher's Exact Test				.011	.007
N of Valid Cases	223				

a. 0 cells (,0%) have expected count less than 5. The minimum expected count is 50,37.

b. Computed only for a 2x2 table

"Purchase of Intended Item" by participants is another dependent variable which a chi-square test will assess in order to see whether there exist statistically significant differences between groups. Bar chart in Figure 15 shows that in treatment group 67 (58.26%) out of 115 participants purchased the item that they have intended to purchase before starting the shopping task. In control group this figure is 44 (40.74%) out of 108 participants. Appendix E shows the cross tabulation figures of the dependent variable *purchase of intended item*.

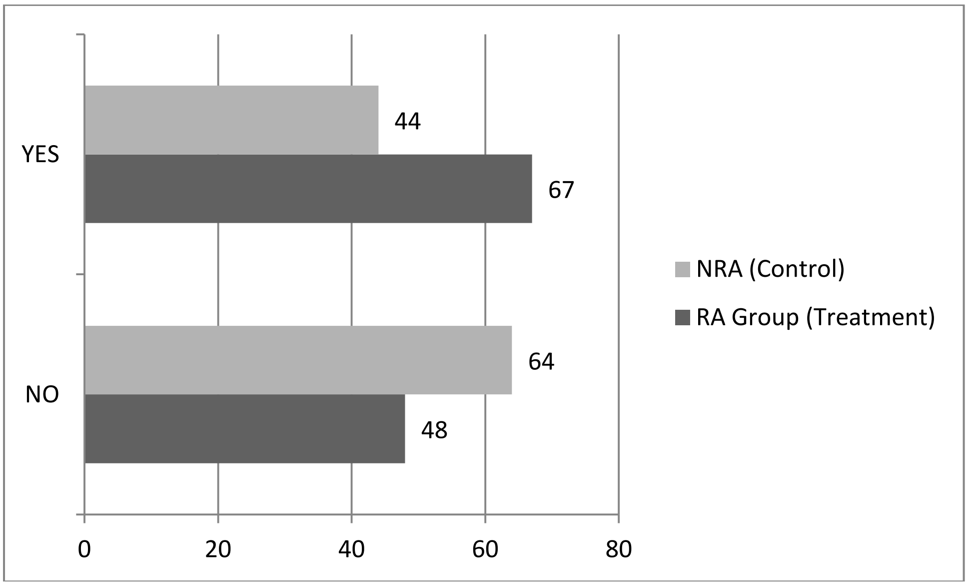

Figure 15 - Purchase of Intended Item

Table 15 shows that chi square statistic (x^2=6.838), degree of freedom (df=1) and asymptotic significance (p=0.009).“Asymp.Sig.” value (p=0.009) is less than the predetermined alpha level of significance (p=0.05). Therefore, it can be concluded that difference between control and treatment group is statistically significant at predetermined alpha level 0.05. These results support the hypothesis 4 which states that “*Use of RA is positively related to purchase of intended item of user”.*

Table 15 - Chi-Square Tests (Purchase of Intended Item)

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	6.838[a]	1	.009		
Continuity Correction[b]	6.156	1	.013		
Likelihood Ratio	6.874	1	.009		
Fisher's Exact Test				.011	.006
N of Valid Cases	223				

a. 0 cells (,0%) have expected count less than 5. The minimum expected count is 53,76.

b. Computed only for a 2x2 table

CHAPTER VI

DISCUSSION AND CONCLUSION

This chapter presents the discussion of results derived from statistical analysis, the conclusion of the study and the recommendations for future research.

6.1 Discussion

There are several papers in the literature analyzing the impact of recommender systems on online consumer behavior. Most of them use subjective methods (e.g., questionnaire) to assess the influence of such intelligent agents on consumer behavior. What makes this study different than previously conducted researches is that this study utilized only objective measures to test study hypotheses. That is, rather than asking participants to express their opinions and feelings about shopping process by asking them to fill questionnaire, developed shopping systems tracked participants actions during the simulated shopping task and saved these logs to the database. Later, all these log data have been analyzed by utilizing necessary statistical methods and tools.

Disadvantages of using subjective methods is that evaluation process starts after event finishes which makes participants to forget some important aspects of the event they are evaluating. Another disadvantage is that participants tend to superficially answer some questionnaire items or they tend to skip some questions that take too long to read. In order to overcome such issues and obtain more reliable results from the investigation, shopping system log data have been used instead of using classic questionnaire approach.

This study assessed the influence of knowledge-based e-commerce product recommender systems on online-consumer decision making process. Consumers' shopping duration, purchase of intended item, effort spent in searching product and their decision quality has been assessed. Proposed hypotheses of the study have been tested and the results are given in Table 16.

Table 16 - Summary of findings of the hypotheses

Hypotheses	Independent Variable	Dependent Variable	Result
H1: There is a negative relationship between the use of RA and shopping duration of user	RA Use	Shopping Duration	Accepted
H2: There is a negative relationship between the use of RA and search effort of user	RA Use	Search Effort	Accepted
H3: There is a positive relationship between the use of RA and decision quality of user	RA Use	Decision Quality	Accepted
H4: There is a positive relationship between the use of RA and purchase of intended item by user	RA Use	Purchase of Intended Item	Accepted

Results of statistical tests showed that the there is negative relationship between use RA and shopping duration of participants. That is, in simulated shopping task RA assisted participants spent statistically significantly less time than non-RA assisted participants. This is the same finding as the findings of Hostler et al. (2005) and Pedersen’s (2000). On the other hand, this finding contradicts with study findings of Olson & Widing (2002) which showed that RA assisted participants had longer actual and perceived decision time.

It is clear in the statistical tests that use of RA negatively and significantly influenced the search effort of participants in simulated shopping session. RA users viewed and analyzed statistically significantly fewer pages than non-RA users. This statistical result is similar to the study findings of Haubl & Trifts (2000) which showed that the participants who have been assisted by recommender agents analyzed substantially fewer product details than the ones who have not been assisted by such intelligent systems.

Statistical tests have indicated that use of RA positively and significantly influenced the decision quality of participants in simulated shopping session. There are several methods to measure decision quality of participants including objective and subjective methods. The method used in this study is an objective one and measured participants confidence level in their decisions. In simulated shopping session the number of participants who changed their mind and purchased another random product when given a chance was statistically significantly less in the existence of RA than absence of such intelligent system. This is the same finding as the findings of Haubl & Trifts (2000) and Olson & Widing (2002).

In the light of statistical tests, it can be understood that use of RA positively and significantly influenced the purchase of intended item by participants. Before starting to the simulated shopping task participants are presented and informed about different photography types. Then participants are asked for which type of photography they intend to use the camera they will purchase. After the simulation, category of the purchased camera is compared with the initial intended camera category of the participants. It is statistically proved that that the number of participants who purchased the camera that matches to their initial intention is statistically significantly more in the existence of RA than absence of such intelligent systems.

6.2 Conclusion

This study aimed to assess the influence of online recommender system on online consumer decision making process. Results of the study showed that there are significant influences of recommender agents over consumers' shopping duration, search effort, decision quality (confidence in decision) and purchase of intended item.

Shopping duration and searching effort of participants can be considered as an overall effort measure while shopping over internet. Statistical tests showed that participants who have been assisted by RA had statistically significantly less shopping time and searching effort than non-RA assisted participants. This means that participants who utilize RA for their shopping activities exert less effort by saving time and searching through fewer pages and details.

In this study, decision quality (confidence in decision) and purchase of intended item by participants were considered as an overall decision quality measure. Results of the statistical tests showed that the number of participants who were not confident in their final selections (item to purchase) were statistically significantly less in existence of RA than non-RA. In other words, most of the participants who were assisted by RA considered their final selections to be ideal and preferred not to switch to randomly recommended item by the system. Besides to confidence in decision, purchase of intended item by participants is used as another measure of overall decision quality. Statistical tests also showed that the number of participants who purchased the product that they initially intended to purchase were greater in the existence of RA than none existence of such systems.

Considering all these points mentioned above, it can be concluded that recommender agents improve consumer decision making process by decreasing shopping duration and searching effort and by increasing decision quality and purchase of intended item by online consumer.

6.3 Contribution of the Study

Internet shopping is growing at an increasing rate every passing year. Online sellers provide very large amount of items from convenience products (i.e. food, cleaning, personal care) to specialty products (i.e. automobile, real estate) to the potential customers located in different countries around the world. Customers shopping over internet usually encounter difficulties in choosing the right product or services for themselves among the given alternatives. In order to overcome these difficulties and facilitate online shopping different kind of recommender systems developed in the last decade. This study analyzed the impact of one kind of developed recommender systems (knowledge-based) on consumer decision making process. Results of this study contributes to the relevant literature by proving that such intelligent systems improves decision making process by increasing consumers' decision quality and decreasing the consumers' overall effort while shopping over internet. Online sellers can consider results of this study as additional evidences of the potential benefits of integrating such intelligent systems to their website in order to better serve to their customers.

6.4 Limitations and Further Research

Several limitations exist in this study. Firstly, this study analyzed only one type of recommender agent's (knowledge-based) influence on consumer decision making process. Therefore, readers should be careful while generalizing results of this study to other type of recommender agents.

Secondly, since this research is conducted at METU, participants of this study were limited to university students. It might be useful to replicate this study with different population groups.

Thirdly, this study utilized simulated shopping environment; that's, participants pretended as if they were really purchasing the product from online store. Replicating this study in real life situations might bring out interesting results.

This study has not considered the possible effects of moderating factors on the study results. Possible moderating factors can be participants' product expertise, product type, product complexity, risks involved in purchasing given product, participants' familiarity with recommender systems and etc. It is recommended that future studies analyze the impact of recommender agents on consumer decision making process by considering the moderating factors mentioned above.

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APPENDICES

APPENDIX A - DESCRIPTIVE STATISTICS OF SHOPPING DURATION

Descriptives

	Type			Statistic	Std. Error
Shopping Duration	NRA	Mean		278.75	4.777
		95% Confidence Interval for Mean	Lower Bound	269.28	
			Upper Bound	288.22	
		5% Trimmed Mean		278.07	
		Median		277.00	
		Variance		2464.432	
		Std. Deviation		49.643	
		Minimum		167	
		Maximum		440	
		Range		273	
		Interquartile Range		69	
		Skewness		.300	.233
		Kurtosis		.576	.461
	RA	Mean		189.64	3.837
		95% Confidence Interval for Mean	Lower Bound	182.04	
			Upper Bound	197.25	
		5% Trimmed Mean		188.22	
		Median		188.00	
		Variance		1693.407	

	Std. Deviation	41.151	
	Minimum	110	
	Maximum	310	
	Range	200	
	Interquartile Range	60	
	Skewness	.401	.226
	Kurtosis	-.030	.447

APPENDIX A (cont.) - DESCRIPTIVE STATISTICS OF SEARCH EFFORT

	Type			Statistic	Std. Error
Search Effort	NRA	Mean		24.89	.615
		95% Confidence Interval for Mean	Lower Bound	23.67	
			Upper Bound	26.11	
		5% Trimmed Mean		24.74	
		Median		25.00	
		Variance		40.810	
		Std. Deviation		6.388	
		Minimum		12	
		Maximum		43	
		Range		31	
		Interquartile Range		9	
		Skewness		.351	.233
		Kurtosis		.011	.461
	RA	Mean		16.10	.317
		95% Confidence Interval for Mean	Lower Bound	15.48	
			Upper Bound	16.73	
		5% Trimmed Mean		16.02	
		Median		16.00	
		Variance		11.550	
		Std. Deviation		3.399	
		Minimum		8	
		Maximum		28	
		Range		20	
		Interquartile Range		4	
		Skewness		.410	.226
		Kurtosis		.960	.447

APPENDIX B - NON-PARAMETRIC LEVENE'S TEST

		Sum of Squares	df	Mean Square	F	Sig.
Computer Experience	Between Groups	.176	1	.176	.465	.496
	Within Groups	83.897	221	.380		
	Total	84.074	222			
Frequency of Computer Usage	Between Groups	.399	1	.399	1.871	.173
	Within Groups	47.139	221	.213		
	Total	47.539	222			
Frequency of Internet Usage	Between Groups	.058	1	.058	.681	.410
	Within Groups	18.853	221	.085		
	Total	18.911	222			
Frequency of Visiting Shopping Websites	Between Groups	.002	1	.002	.005	.941
	Within Groups	83.238	221	.377		
	Total	83.240	222			
Frequency of Purchasing Product Online	Between Groups	.078	1	.078	.320	.572
	Within Groups	53.752	221	.243		
	Total	53.830	222			
Camera Usage Experience	Between Groups	.052	1	.052	.262	.609
	Within Groups	43.952	221	.199		
	Total	44.004	222			
Knowledge Level of Camera Technology	Between Groups	.197	1	.197	1.117	.292
	Within Groups	38.949	221	.176		
	Total	39.146	222			
Camera Usage Frequency	Between Groups	.000	1	.000	.001	.974
	Within Groups	60.407	221	.273		
	Total	60.407	222			

APPENDIX C - MEAN RANKS OF PRETEST ITEMS

	Type	N	Mean Rank	Sum of Ranks
Computer Experience	RA	115	110.82	12744.00
	NRA	108	113.26	12232.00
	Total	223		
Frequency of Computer Usage	RA	115	113.83	13090.00
	NRA	108	110.06	11886.00
	Total	223		
Frequency of Internet Usage	RA	115	116.92	13446.00
	NRA	108	106.76	11530.00
	Total	223		
Frequency of Visiting Shopping Websites	RA	115	108.43	12469.00
	NRA	108	115.81	12507.00
	Total	223		
Frequency of Purchasing Product Online	RA	115	112.54	12942.00
	NRA	108	111.43	12034.00
	Total	223		
Knowledge Level of Camera Technology	RA	115	111.96	12875.00
	NRA	108	112.05	12101.00
	Total	223		
Camera Usage Experience	RA	115	111.51	12823.50
	NRA	108	112.52	12152.50
	Total	223		
Camera Usage Frequency	RA	115	111.67	12841.50
	NRA	108	112.36	12134.50
	Total	223		

APPENDIX D - MANN-WHITNEY U TEST (PRETEST ITEMS)

	Computer Experience	Frequency of Computer Usage	Frequency of Internet Usage	Frequency of Visiting Shopping Websites
Mann-Whitney U	6074.000	6000.000	5644.000	5799.000
Wilcoxon W	12744.000	11886.000	11530.000	12469.000
Z	-.292	-.462	-1.304	-.893
Asymp. Sig. (2-tailed)	**.770**	**.644**	**.192**	**.372**

a. Grouping Variable: Type

	Frequency of Purchasing Product Online	Knowledge Level of Camera Technology	Camera Usage Experience	Camera Usage Frequency
Mann-Whitney U	6148.000	6205.000	6153.500	6171.500
Wilcoxon W	12034.000	12875.000	12823.500	12841.500
Z	-.143	-.011	-.126	-.084
Asymp. Sig. (2-tailed)	**.886**	**.991**	**.900**	**.933**

a. Grouping Variable: Type

APPENDIX E - CROSSTABULATIONS TABLES

			Decision Quality		Total
			No	Yes	
Type	RA	Count	71	44	115
		Expected Count	61.4	53.6	115.0
	NRA	Count	48	60	108
		Expected Count	57.6	50.4	108.0
Total		Count	119	104	223
		Expected Count	119.0	104.0	223.0

			IntendedItem		Total
			No	Yes	
Type	RA	Count	48	67	115
		Expected Count	57.8	57.2	115.0
	NRA	Count	64	44	108
		Expected Count	54.2	53.8	108.0
Total		Count	112	111	223
		Expected Count	112.0	111.0	223.0

APPENDIX F - ETHICAL CLEARANCE

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26 Şubat 2013

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Gönderen : Prof. Dr. Canan Özgen
IAK Başkan Yardımcısı

İlgi : Etik Onayı

Danışmanlığını yapmış olduğunuz Bilişim Sistemleri Bölümü Yüksek Lisans öğrencisi Farid Huseynov'un "E-Ticarette Kullanılan Bilgi Tabanlı Öneri Sistemlerinin Online Müşterilerin Karar Sürecine Etkileri" isimli araştırması "İnsan Araştırmaları Komitesi" tarafından uygun görülerek gerekli onay verilmiştir.

Bilgilerinize saygılarımla sunarım.

Etik Komite Onayı

Uygundur

26/02/2013

Canan Özgen

Prof.Dr. Canan ÖZGEN
Uygulamalı Etik Araştırma Merkezi
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ODTÜ 06531 ANKARA

APPENDIX G – DEMOGRAPHIC AND PRETEST SURVEY ITEMS

Nickname:..

{The one you used in the simulated online shopping survey}

1. Age: ....
2. Gender: F☐ M☐
3. For how many years have you been using a computer: ....
4. How many hours do you spend on computer in a day:
    - o 1 hour or less
    - o 2 – 3 hours
    - o 4– 6 hours
    - o More than 6 hours
5. How many hours do you spend on internet in a day:
    - o 1 hour or less
    - o 2 – 3 hours
    - o 4– 6 hours
    - o More than 6 hours
6. How often do you visit any kind of online shopping websites:
    - o Always
    - o Often
    - o Frequently
    - o Occasionally
    - o Rarely
7. How often do you purchase a product from online shopping websites:
    - o Extremely often
    - o Often
    - o Moderately often
    - o Rarely

- Never

8. Grade your knowledge level with digital camera technology?

   {Grade from 1[very little] to 5[advanced]}

   ....

9. What is your level of digital camera usage experience?

   {Grade from 1[very little] to 5[advanced]}

   ....

10. How often do you use your digital camera?
    - Always
    - Often
    - Frequently
    - Occasionally
    - Rarely

APPENDIX H - SHOPPING SYSTEM LOG RECORD SHEET

Nickname
Initial Objective
Purchased Item
Decision Changed
Start Time
Finish Time
Page View
Help View
Duration