Adaptive Decision Support System (ADSS) for B2C E-Commerce

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ABSTRACT
This paper covers the research problem of supporting users' decision making in E-Commerce systems with complex choices, and design of an Adaptive Decision Support System (ADSS) which matches the appropriate tool support and decision strategy advice to the user's preferences and motivations. A preliminary requirements investigation will be described which used an adapted Wizard of Oz approach to test users' reaction to mock-ups of the ADSS with and without system advice. The requirements study tested users' reaction to the proposed tools and whether they were influenced by the system advice. This discussion will be followed by a description of the design and development of the ADSS and its architecture. The paper concludes with plans for future research.

Categories and Subject Descriptors
H.4.2 [**Information Systems Application**]: Types of System – *decision support system*
K.4.4 [**Computer and Society**]: Electronic Commerce

General Terms
Decision support system, E-Commerce

Keywords
Adaptive decision support system, B2C E-Commerce, decision aid.

1. INTRODUCTION
The advent of Electronic Commerce (E-Commerce), from the Business to Consumer (B2C) perspective, has opened new opportunities for sales, as well as new issues to address in the design of E-Commerce systems. In E-Commerce, buyers benefit from convenient access to information and commerce while sellers benefit from selling to consumers anytime and anywhere with low bricks-and-mortar and intermediary costs. Despite these benefits for both buyers and sellers, the current conversion rates are still very low (2%-6%) [13].

With poor usability of most E-Commerce sites, Nielsen [31] conducted a study in which users made 496 attempts to perform different tasks on 20 large and small E-Commerce sites. The result of this study showed that only 56% of those attempts were successful. In other words, sellers are losing a large percentage of potential sales simply because their sites are confusing and difficult to use.

Furthermore, the proliferation of online products provides a wide variety of choices for the consumer in selecting a product that meets his/her preferences. However, the large number of choices available on the web overloads consumers and they often find it difficult to make a final choice of a product. Therefore, one crucial task for E-Commerce systems is to help buyers select products with a minimal amount of effort and time [39].

Since E-Commerce sites are accessed by diverse types of consumers with different backgrounds, preferences and expertise, their usability should satisfy different consumer needs and preferences in the process of product search and choice.

Traditional search facilities in E-Commerce systems use information retrieval techniques to retrieve all products that match the consumer query and display them as a list sorted by their relevance values. The results could be displayed in multiple pages where the consumer struggles to find the best product that matches his needs and preferences among large results sets. Consequently, consumers become confused by information overload and poor presentation of information which do not take into account different consumer needs, expertise and product complexity [30].

Studies from economics and psychology have shown that the individual has bounded rationality when making decisions due to his/her limited knowledge and computational capacity [47]. Therefore, one crucial task for E-Commerce systems is to help buyers choose the products they prefer with a reasonable amount of effort and time. As a result, it is an essential task to provide decision assistance for the end user to determine the target product both accurately and efficiently

In summary, due to the information overload in the Internet, product proliferation, product complexity and poor design of search facilities in E-Commerce systems, the problem of consumer confusion is becoming a major obstacle in finding products and making purchase decisions which satisfy the consumer's needs.

The remainder of this paper is organized as follows: Section 2 provides a brief background of related research. Section 3 introduces the ADM theory followed by the theoretical framework of ADSS. The discussion of the methods and results of the requirement study is presented in Section 4. Section 5 describes the design of the ADSS system and its architecture. Section 6 concludes with plans for future research.

2. LITERATURE REVIEW

This section provides a brief background to five different areas of research that attempt to support consumers in the decision-making process using different approaches.

2.1 Business and Marketing

There is ongoing marketing research in the area of consumer confusion caused by product proliferation and information overloading which causes consumers to abandon or postpone their purchase decisions [30, 51]. In this research, three components that confuse consumers were identified, i.e. similarity of products, ambiguous and misleading information about products, and information overloading. Another component resulting from website design is operational confusion caused by poor design of product presentation, search and choice strategies.

Substantial research efforts have attempted to understand the consumer purchase decision-making process in order to build better and more successful E-Commerce systems. In addition, many researchers identified that one of the major problems with E-Commerce systems is that they fail in supporting consumers' needs in the purchase decision-making process [19, 34, 36]. Understanding the consumer purchase decision-making process plays a key role in building successful E-Commerce systems.

The purchase decision-making process [52] is represented by six basic phases (stimulate, consider, search, evaluate, buy and repurchase) that are experienced by all consumers regardless of the type of the products and services offered. Understanding the consumer purchase decision-making process could guide designers and researchers to build more effective E-Commerce systems that provide the necessary support for consumers. As a result, many studies have attempted to conceptualize and define consumer Decision Support Systems (DSS) that provide different support (e.g. banner advertisements, marketing email, recommendation, virtual catalogues and FAQs) to consumers in each purchase decision-making process [14, 34, 53]. They argue that consumers with DSS will perceive better information quality, faster decision, more satisfaction and higher intention to use the system in the future than without such support.

Two marketing theories [41] attempt to understand the consumer decision-making process. The first theory is called Consideration, where the consumers establish a sub-set of brands from which the decision-making strategies are applied in high-volume similar products. The second theory is called Involvement, in which the amount of cognitive effort applied to the decision-making process is directly related to the level of importance that the consumers place on purchase of the specific product. In other words, people make their decision differently when they are involved in buying a high-value product like a house compared to the situation of buying a low-value product like a book.

Several researchers [19, 33, 34] have studied the effect of consumer decision support systems on the online shopping environment and its importance in providing an effective support to cope with information overload and product complexity. Recommendation Agent (RA) and Comparison Matrix (CM) tools are proposed in the information search/choice stages of the decision process to assist consumers. They argue that individuals tend to use two-stage processes to reach their final decisions in complex environments: RA is used for the initial screening of available alternatives to identify a sub-set of the most promising alternatives, and CM is used for the in-depth comparison of selected options to help users make actual decisions. They conclude that such tools improve the consumer decision-making process, and the availability of such DSS in online environments will enhance the ability of individuals to identify the products that best match their preferences.

2.2 Adaptive User Interfaces and User Modeling

Adaptive user interfaces and personalization based on Information filtering provide users with a sub-set of relevant information rather than flooding them with all the information available. The need for information filtering techniques has been rapidly increasing during the last decade due to the information overload problem [9, 12, 15, 27, 32, 50].

Easy access to large amounts of product information allows consumers to make better purchase decisions. On the other hand, having access to large amounts of information can overload consumers and they may be unable to adequately process the available information. Human decision makers have limited resources for information processing, whether these limits are in memory, motivation or attention [7, 35, 43].

Since E-Commerce systems are accessed by diverse types of consumers with different backgrounds, preferences and expertise, their usability, information and design should satisfy different consumers according to their needs and preferences in the purchase decision-making processes [2, 23].

A response to the problem of information overload in the online environment is the emergence of personalization and recommender systems which provide users with more proactive and personalized information services by modeling individual consumers' preferences [17, 20, 21, 27].

One of the most popular approaches today in recommender systems is collaborative filtering. In this approach, the recommender system requires the user to rate a series of product examples from which it constructs a user profile. Subsequently the system finds other people who have similar profiles to the current user and recommends products that match the current user requirements. Collaborative filtering examples in the Internet are Amazon.com in selling books and other items, and Ringo in movies [8, 17, 45].

Another approach in personalization is customizing shopping tools based on consumers' product knowledge [25]. The authors argue that consumers with low product knowledge (inexperienced) may not be able to use decision tools as well as consumers with high product knowledge (experienced) because inexperienced consumers allocate their cognitive effort to learning the product attributes rather than using the tool effectively. On the other hand, decision tools may effectively guide the decision making of inexperienced consumers, but be perceived as too limited by experienced consumers. As a result, the authors argue from their experiment results that adapting shopping decision tools to the degree of consumers' knowledge/experience will provide effective support for consumers.

2.3 B2C E-Commerce DSS

According to Mallach [28], a Decision Support System (DSS) is an interactive computer-based system intended to help users to make their decisions.

Many researchers [3, 7, 24, 35] have studied the human decision-making process in offline environments. Their research in behavioral decision theory describes people's adaptive decision behavior. In the online environment, Zhang and Pu [54] argue that adaptive decision behavior still exists, but the classical effort-accuracy framework needs to be adjusted. Since the decision maker's cognitive effort is still required, it can be significantly decreased by having computers carry out most of the work automatically. However, the decision makers must spend some effort to explicitly state their preferences to the computer interface.

An investigation [22] into whether consumers adapt their decision strategies on E-Commerce websites in the presence of decision support technology compared two websites: CompareNet (compare.net) and Jango (jango.com). CompareNet used a comparison matrix (CM) to display products side by side based on a set of attributes (table display); in contrast, Jango simply presented the alternatives in a traditional ranked list. Consumers employed more compensatory decision strategies when using CompareNet, and they were also more satisfied with it than with Jango. Consumers also used more compensatory strategies with a smaller number of alternatives (fewer than 30). Since the more compensatory decision strategies consumers use are directly related to making more accurate decisions, the authors suggested that website designers should use decision technology to support alternative comparison using CM.

A decision tool that supports complex trade-offs called example-based search, has been developed by Pu et al. [38, 39]. The authors compare the traditional ranked list tool with an example-based search tool (also called example critiquing) and demonstrate that example-based search is comparable to ranked lists on simple tasks, but significantly reduces the error rate and search time when complex trade-offs are involved. They argue that supporting trade-offs especially in complex tasks could significantly support consumers in making their decision and improve satisfaction.

Another decision tool called anchoring examples [55] proposes a new approach of supporting users by accumulating the users' preferences gradually by showing a small set of alternative samples and then asking the user to select the best one. Subsequently, the system analyzes the users' preferences according to their selection and generates new sets of samples to guide the elicitation process until the final choice is reached. As the anchoring examples shown are only a small fraction of the total available alternatives, the decision maker's effort can be saved.

2.4 Information Visualization

Exploring large data spaces has remained a challenging task for information visualization researchers [10]. Since people have a massive capacity for processing visual information, many interactive information visualization displays have been invented to give users more control to explore complex data spaces more effectively.

Shneiderman [46] presented a novel approach called dynamic queries manipulation that enables users to cope with information overload by allowing them to explore the data space and filter out information rapidly with slider controls. This concept was tested in three different displays (chemical table of elements, computer directories, and a real estate database) and showed significant performance improvements and user satisfaction.

The concept of dynamic query filters (i.e. sliders and buttons) with visual displays (i.e. scatterplot display and attribute explorer) to support users in coping with information overload has been proposed by several authors [1, 16, 49]. FilmFinder is one of the examples developed using a movie database with two-dimensional scatterplot display and dynamic query filters that support rapid refinement on the display output to promote more search input from the users. The dynamic query technique has been proven to provide an effective way of presenting information, powerful filtering tools, and easy to control user query for both novice and expert users.

2.5 Computer as a Social Actor

A recent study by Riegelsberger et al. [42] illustrated how users respond more effectively and more naturally to rich media representations (video, audio, avatar, photos) compared to textual messages and showed that video followed by audio gives the user the most detailed insight into expertise and trust.

Reeves and Nass [40] showed from a series of experiments that people treat and respond to human representation on rich media (i.e. computers and television) in just the same way as they treat and respond to other people in everyday social interactions. The computers and televisions are treated as social actors, and the rules which people apply to everyday social interaction apply equally well to their interactions with computer-mediated human representations. Fogg [18] has studied computers as a persuasive technology (Captology). He showed how a persuasive computer with interactive technology can change or attempt to change a person's attitudes or behaviors. One of the examples of Captology uses various types of Embodied Conversational Agents (ECAs) or Avatars that attempt to encourage or persuade users to perform specific tasks.

The persuasive power of rich media representation like ECAs could emulate human behaviors and build trust between the user and computer if ECAs can interact as in human-human conversation. Pelachaud and Bilvi [37] present a computational model for the creation of non-verbal behaviors associated with speech toward building more natural ECAs that can emulate human behaviors of facial expression, body gesture and speech. Substantial attempts [5, 6, 11] have been made to facilitate the creation of ECAs to provide users with more natural information delivery and relationships building trust to emulate the experience of real human face to face interactions.

Keeling et al. [26] investigated the types of ECAs that are appropriate for different E-Commerce websites using data from 30 Internet shoppers' interviews. They mainly focused on matching what type of ECA (e.g. cartoon-like agent and human-like agents) is appropriate for the purpose of the website and type of users who visit the website. They argue that great care should be taken in matching ECAs with websites not only in the physical characteristics of the ECA but also in the goals and motivations of the consumers.

2.6 Summary

The need for decision support in online shopping environments to help consumers and improve decision confidence and satisfaction is well understood. A DSS should provide an effective support for consumers in terms of information display, searching strategies, and appropriate advice for different consumers in different contexts and scenarios.

The aim of the recommender systems and personalization in E-Commerce is to help consumers in coping with the information overload problem. However, recommender systems and personalization require a relatively high amount of data to produce a reliable user model. Many researchers have attempted to improve system recommendations by creating new knowledge structures to satisfy user goals and at the same time reduce the amount of data required to prevent annoying users in the process of information gathering.

Since the aim of this study is to support consumers in decision making and the potential of ECAs to change people's attitudes and behavior, ECAs will be embedded into the ADSS interface to deliver the system advice in a persuasive manner. The system advice will be based on Adaptive Decision Making (ADM) theory [35] to support users when they are in the search and choice stages of the purchase decision-making process.

Since we believe that adaptive decision behavior exists, different decision tools that support different decision strategies will be appropriate for different scenarios and contexts that involve different users and different product domains. The advisor will play the key role in ADSS to advise the users in tool selection and provides advice related to the decision strategies, product domain and decision tool use.

3. CONCEPTUAL FRAMEWORK

As the product or service information provided by the E-Commerce system is far beyond any individual's bounded rationality [47], it is impossible to select the best item by hand. It is vital to understand how people adapt their strategies for solving decision problems according to the task demands and the limited capacity of information processing they have to build an effective DSS. As a result, the most sophisticated and well defined adaptive decision theory, the Adaptive Decision Making (ADM) theory [35], is chosen to form the basis for ADSS.

The development of ADSS could increase decision making efficiency by combining the knowledge obtained from the ADM theory [35], which describes people's decision behavior; and computer technology, which can be used to automate some aspects of the decision process and provide different ways of presenting information that could be processed more effectively. ADSS will also help users to learn better decision making skills by using different decision tools and advice in different scenarios.

3.1 Overview of Adaptive Decision Maker (ADM) Theory

How people make preferential choices and judgments among a set of alternatives has been of great interest to psychologists, economists, and other researchers [3, 7, 24, 35, 47, 48].

One of the most influential theories, the Adaptive Decision Making (ADM) theory, describes how people adapt their strategies for solving decision problems according to the task demands and complexities they face, and to the limited capacity of information processing they have [35]. In particular, the ADM theory describes a set of strategies that people might use for making decisions and an indication of the task variables which may lead to one strategy being chosen over another. ADM theory describes how people adapt their decision strategies by trading-off accuracy and their cognitive effort to the demands of the tasks (see Figure 1).

In Figure 1, the decision problem consists of task variables which are general characteristics of the decision problem (e.g. time pressure, number of alternatives and number of attributes) and context variables which are related to particular values of alternatives (i.e. similarity of alternatives). The decision maker's cognitive effort and prior knowledge interacts with the social context to justify and reason to others about why and how the final decision is made. The decision strategy selection is an adaptive response to those variables, in an effort-accuracy framework.

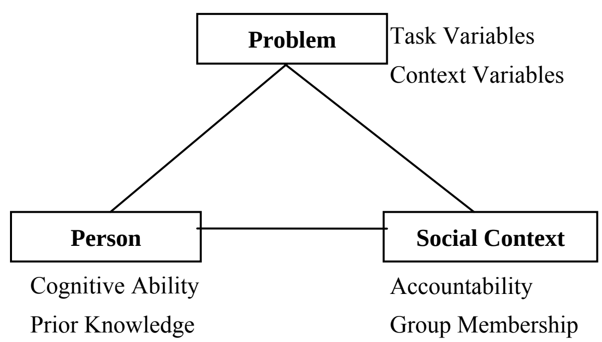

Figure 1: Contingent Strategy Selection - Adapted from [35]

According to ADM theory, individuals differ according to whether they use alternative-based versus attribute-based processing in the decision environment. When people are confronted with few alternatives, they tend to use compensatory strategies (e.g. WADD (Weighted Additive)) in which they compensate good values in some attribute for poor values in other attributes. However, with more alternatives, people respond by simplifying their decision strategy using non-compensatory strategies (e.g. EBA (Elimination by Aspect) and LEX (Lexicographic)) which are simple strategies to filter alternatives based on one or a few attributes of the information.

In general, processing in complex decision problems is more attribute-based early in the process and more alternative-based later in the process where trade-offs can be used. In addition, decision quality decreases with increase in the number of alternatives and attributes after a certain level of complexity has been reached. People can be overloaded with information due to their limited information processing capacity.

As a result, people respond to complex information environments by simplifying their decision strategy using non-compensatory strategy and focus their attention on the most important information (called selectivity) to avoid getting distracted by irrelevant or less important information. Furthermore, people make their decisions differently under time pressure. With less time available, people respond by selective attention to more important information and simplifying their decision strategy with non-compensatory processing.

Since decision makers have limited information processing capacity, they often do not have well defined preferences but they construct them using a selection of strategies based on the task demands and complexities they face [4]. The construction process is formed by the interaction between the properties of human information processing and the properties of the decision task, leading to highly contingent behavior [35].

3.2 Conceptual Framework

People tend to adapt their decision strategies according to the demand of the task they face and to their limited information processing. However, what if people are confronted with computerized decision tools that perform extensive calculation and processing on behalf of the user? How do people adapt to the decision tools available in different product domains? What are the effects of advice on people in different domains and scenarios? Do people use different search strategies in the presence of decision technology?

This research will attempt to answer these questions and show the effect of ADSS on user adaptive behavior and how advice can support users in different product domains and scenarios.

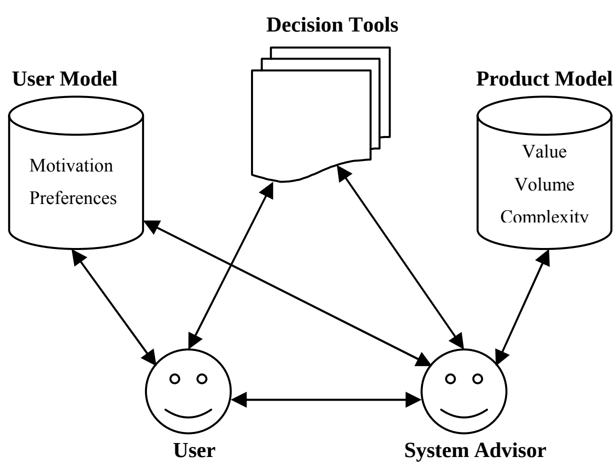

Figure 2: Conceptual Framework of ADSS

Figure 2 shows the basic concept of ADSS framework, where lists of decision tools are recommended by the system advisor according to the Product model and User model. The system advisor represents the core of the framework that uses the decision table, the user model and the product model to recommend appropriate decision tools to the user and also may provide other kinds of decision advice.

3.2.1 User Model

The user model stores the consumer's level of motivation (high, moderate and low) and the level of preferences (well-defined, partially-defined, and undefined) to be used by the system advisor for different product domains. In addition, it keeps track of the user's usage of decision tools including the frequency and the duration of use. This information will be used by the system advisor to capture the user experience and consequently recommend a more advanced tool to the user.

3.2.2 Product Model

The product model captures the product domain information that affects the decision making strategy of consumers. It consists of product value, volume and complexity. The product could either be high value, such as cars, houses, and jewelry, or low value, such as books, videos, and groceries. This information is needed because people make their decision differently when they buy high-value compared to low-value products. The second and third variables of the model are the product volume which is used to hold the number of available alternatives for each product domain, and the product complexity which is used to hold the number of attributes for each product domain.

3.2.3 Decision Tools

One crucial task for E-Commerce systems is to help buyers find products that not only satisfy their preferences but also reduce their search effort. As a result, six decision tools are proposed following the requirement analysis study (see Section 4) and the literature survey (see Section 2). These tools use information searching techniques to generate target product(s) choices by eliciting the users' preferences and then supporting users by using different ways of presenting information that allow them to make better decisions.

The six decision tools that will be used in the ADSS framework are the Filtering tool, Best-Value tool, Ranked-List tool, Concept-Map tool, Decision Tree tool, and the Goodness-of-Fit and Weighting tool. The rationale for this choice of tools is summarized as follows:

Scatterplot filtering has proven to be an effective way of presenting information, a powerful filtering tool, and easy to control for both novice and expert users [1]. In addition, CM (Comparison Matrix (table display)) provides an effective way for in-depth comparison of the selected choices to help users make actual decisions [19, 33]. As a result, these tools are combined to create the Filtering tool (Figure 3).

The Best-Value tool is a form of Recommendation Agent (RA) [19, 33] which identifies a sub-set of the most promising alternatives to cope with information overload. The Best-Value tool uses preconfigured SQL query for each product domain to identify the best available alternatives in the domain.

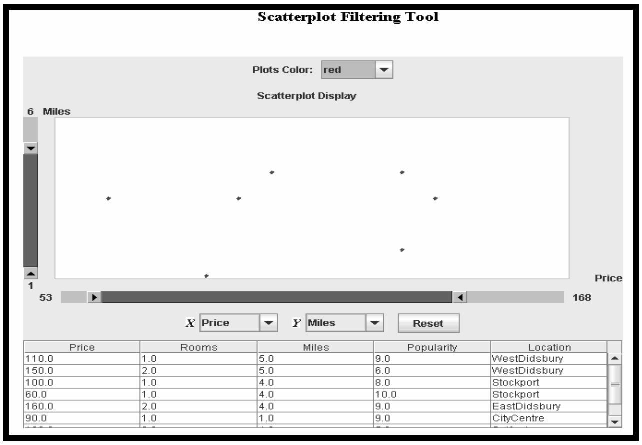

Figure 3: Filtering Tool

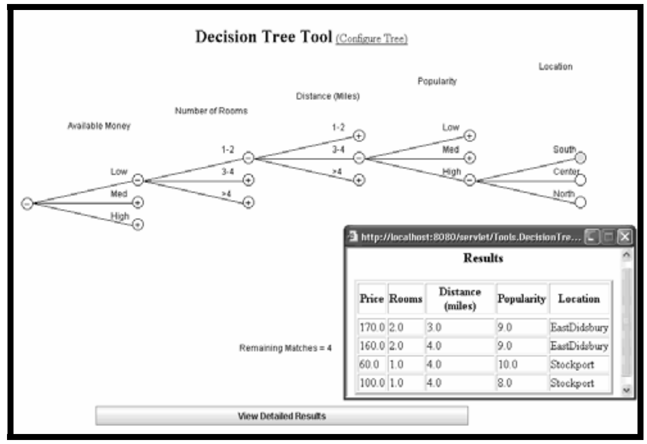

Figure 5: Decision Tree Tool

A Concept-Map tool will display a hierarchical tree structure with or without geographic maps to provide the users with easy ways to navigate the product domains and understand their hierarchy structures and characteristics. The Concept-Map tool combines an overview of the product space and selection arguments to maximize visibility and reduce search (Figure 4).

Decision tree analysis provides an effective structure in which alternative decisions can be easily evaluated [29]. A visual tree display will be used in ADSS to guide the users to find a sub-set of the most promising product choices by following a particular route in the tree hierarchy (Figure 5).

The most traditional tool is the Ranked-List tool in which products that match the user's preferences are shown in increasing order of a quantitative attribute, most often price. This tool has the advantage that it is easy to implement and gives the user an impression of control over the selection process (see Figure 6). Most Ranked-List tools provide decision support only for one attribute of information at a time, although some may rank by multiple attributes. However, when the user's preferences are a combination of multiple and possibly conflicting criteria, the ranked list's efficiency becomes less satisfactory [39]. As a result, a more advanced tool will be used: a Goodness-of-Fit and Weighting tool which allows partial match with the user's preferences and also supports complex trade-offs between attributes using a weighting technique (Figure 7).

These tools are implemented in the ADSS prototype. The diverse types of tools will provide user decision-making support in different scenarios.

3.2.4 System Advisor

The system advisor represents the core of the ADSS framework. It employs the User Model and the Product Model to recommend appropriate decision tools to the users. A decision rules table is used to match the decision tools to the right user profile and the product domain to support users in their decision-making process.

In addition, the system advisor provides product domain advice for users with no defined or partially defined preferences to help them in constructing their preferences and understand the attribute value space especially for high value products. A tutorial on how to use any decision tool is also provided to help use the decision tools more effectively. The system advisor provides decision advice based on the ADM theory, such as advising the users to focus their attention on more important information, especially in complex products, or to perform pairwise comparisons, etc.

The system advisor also monitors the decision tool usage from

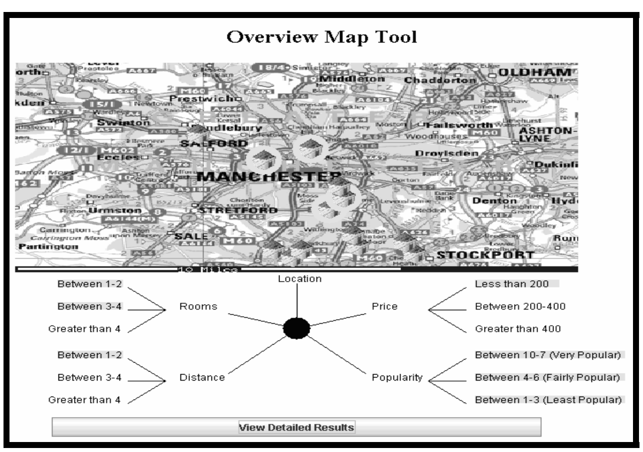

Figure 4: Concept Map Tool

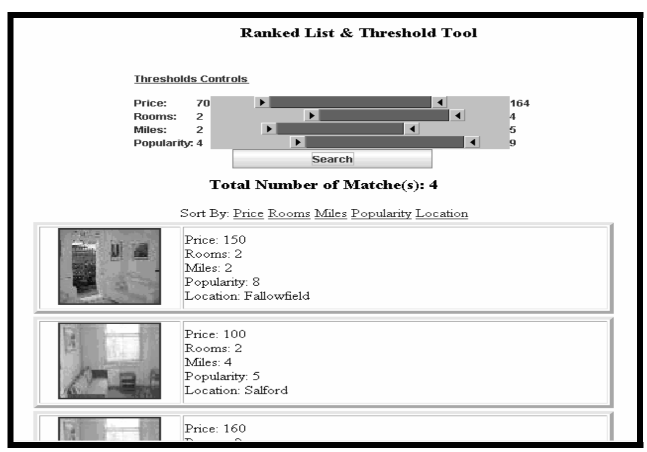

Figure 6: Ranked List & Thresholds Tool

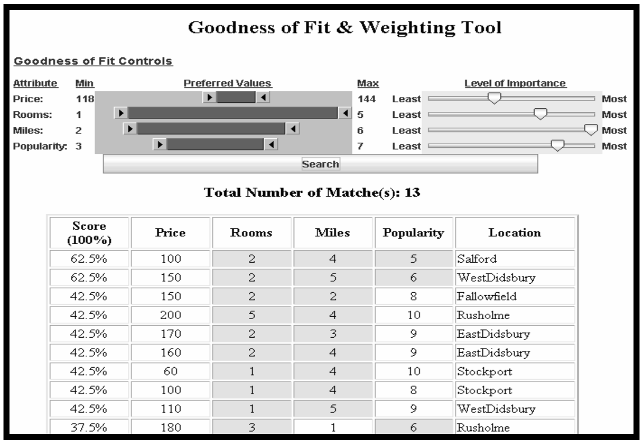

Figure 7: Goodness of Fit and Weighting Tool

the User Model to predict the user's learning of the tools and then recommend a more advanced tool that can provide more support.

The system advisor uses an Avatar to deliver three types of advice to the users: product domain advice that explains the product attributes to the users with no or partially defined preferences. Decision advice explains different decision strategies that could be performed using different tools to make better decisions. These decision strategies are based on ADM theory such as pairwise comparison, selectivity of information, defining thresholds, elimination, satisficing, etc. Third are tools recommendations according to the User Model and Product Model in decision rules table (see Figure 8 for example). See Figure 9 for an Avatar advice example using Microsoft Agents technology with the Filtering tool.

The system advisor attempts to match the right decision tools and advice to the right consumer and product domain in different scenarios. The matching process is based on a preconfigured decision rules table based on the ADM theory. Since delivering advice in a persuasive manner will play a key role in user acceptance, appropriate ECAs/Avatars and dialogues [40] are used for delivering advice to the consumers.

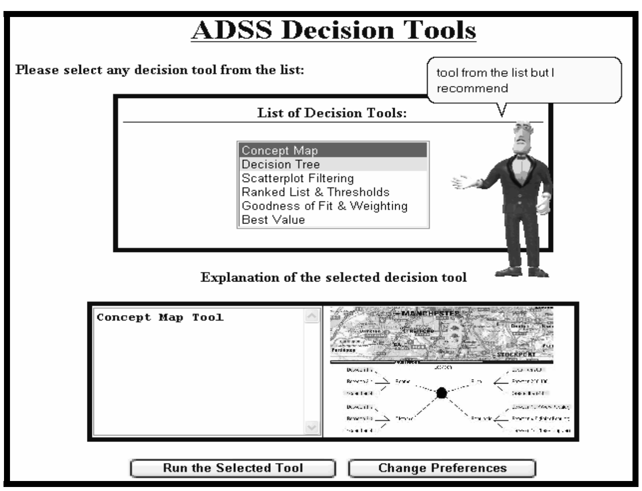

Figure 8: Avatar Tools Recommendations

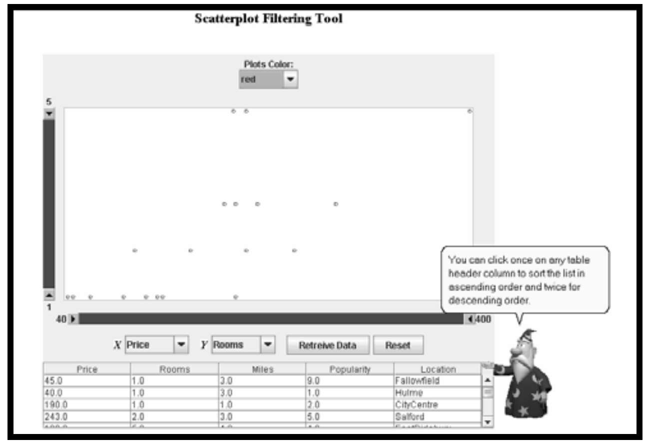

Figure 9: Avatar Advice Example with Filtering Tool

4. REQUIREMENTS ANALYSIS STUDY

This section reports a brief preliminary study of user requirements for ADSS with the mockup design of the system and Wizard of Oz using the scenario-based design method [44].

4.1 Method

Twenty subjects (11 males and 9 females, aged 20 to 39) from the University of Manchester participated in the experiment. Most were postgraduate students and staff, ranging from novice to expert users in their Internet experience. The subjects were paid £10 for their participation. The interview sessions were video taped and lasted between 45 min and 1.25 h, with experimental task durations ranging from 10 min to 20 min.

The main study design was a crossover study where each participant is exposed to two design mockups (List of decision tools without advice and List of decision tools with advice). Seven tool mockups (Best-value, Scatterplot filtering, Table filtering, Goodness-of-fit, Decision tree, Weighted matrix) were used to introduce the concept of tools as well as to capture the subjects' preferences of these tools in different scenarios.

4.2 Design

The study tasks were grouped into two categories (List of tools with and without advice). Four different scenarios were given in each category as summarized in Table 1:

Table 1: Study Design

	Scenarios			
Without advice	Pref. : Well Motiv.:L	Pref. : No Motiv.:L	Pref. : Well Motiv.:H	Pref. : No Motiv.:H
With advice	Pref. : Well Motiv.:L	Pref. : No Motiv.:L	Pref. : Well Motiv.:H	Pref. : No Motiv.:H

Pref. = Defined Preferences, Motiv. = User Motivation, L=Low, H=High

All subjects were asked to select their preferred tool(s) in each scenario before and after advice. In after the advice mode, the Wizard of Oz (experimenter) recommended two decision tools and explained the rationale of each recommended tool in each given scenario. The order of scenarios was given randomly for each subject. The four scenarios were explained as follows: Scenario 1: Imagine that you are under time pressure, with low motivation to explore the product space and you have well-defined preferences; which decision tool(s) will you choose from the following list. Scenario 2: Imagine that you are under time pressure, with low motivation to explore the product space and you have no defined preferences; which decision tool(s) will you choose. Scenario 3: Imagine that you have no restriction on time, are highly motivated to explore the product space and you have well-defined preferences; which decision tool(s) will you choose. Scenario 4: Imagine that you have no restriction on time, are highly motivated to explore the product space and you have no defined preferences; which decision tool(s) will you choose from the list. The ultimate aim of this study was to observe the effect of advising on users' preferences of decision tools in different scenarios.

4.3 Results

Figure 10 visualizes the subjects' selection (ratings) of decision tools on two axes for the four given scenarios. Dark bars in the figure represent subjects' ratings before advice and light bars represent subjects' ratings after advice. The horizontal axis represents the subjects' motivation (low and high) and the vertical axis represent the subjects' defined preferences (No and Well defined). The (*) indicates the recommended decision tools in each scenario and the values with the light colors show that the effects of advice were significant for each particular tool (using binomial test with significant value at p<0.05).

In the first scenario "Low Motivation and No Defined Preferences" (i.e. the user is browsing quickly with no defined goal), Best-Value and Decision Tree tools were recommended in "after advising" mode. The data show clearly how subjects followed the system recommendations and advice. In particular, the effect of advice was significant for the decision tree tool (p=0.046). However, for the Best-Value tool, the effect of advice was not significant (p=0.371). It was common sense to be selected because it was apparent to the subjects that it was the quickest tool.

In the second scenario "Low Motivation and Well Defined Preferences" (i.e. the user is browsing quickly with a defined goal), the subjects' ratings were distributed among the seven tools before advising. However, after advising where Table Filtering and Ranked List were recommended, subjects changed their ratings to follow the system recommendation. The effects of advice on Table Filtering and Decision Tree were significant (p=0 and p=0.031 respectively).

In the third scenario "High Motivation and No Defined Preferences" (i.e. the user is highly motivated to browse and explore with no defined goal), the subjects' ratings were also distributed among the seven tools before advising. However, after advising where Scatterplot Filtering and Table Filtering were recommended, subjects changed their ratings to follow the system recommendation although some subjects still preferred the Goodness-of-Fit tool. This is mostly because the subjects liked the search style of the tool using a partial match with their preferences rather than focusing on the scenario requirements. The effects of advice on Scatterplot Filtering and Ranked List were significant (p=0.015 and p=0.035 respectively).

In the last scenario "High Motivation and Well Defined Preferences" (i.e. the user is highly motivated to browse and explore with a defined goal), the subjects' ratings where distributed among the seven tools before advising. However,

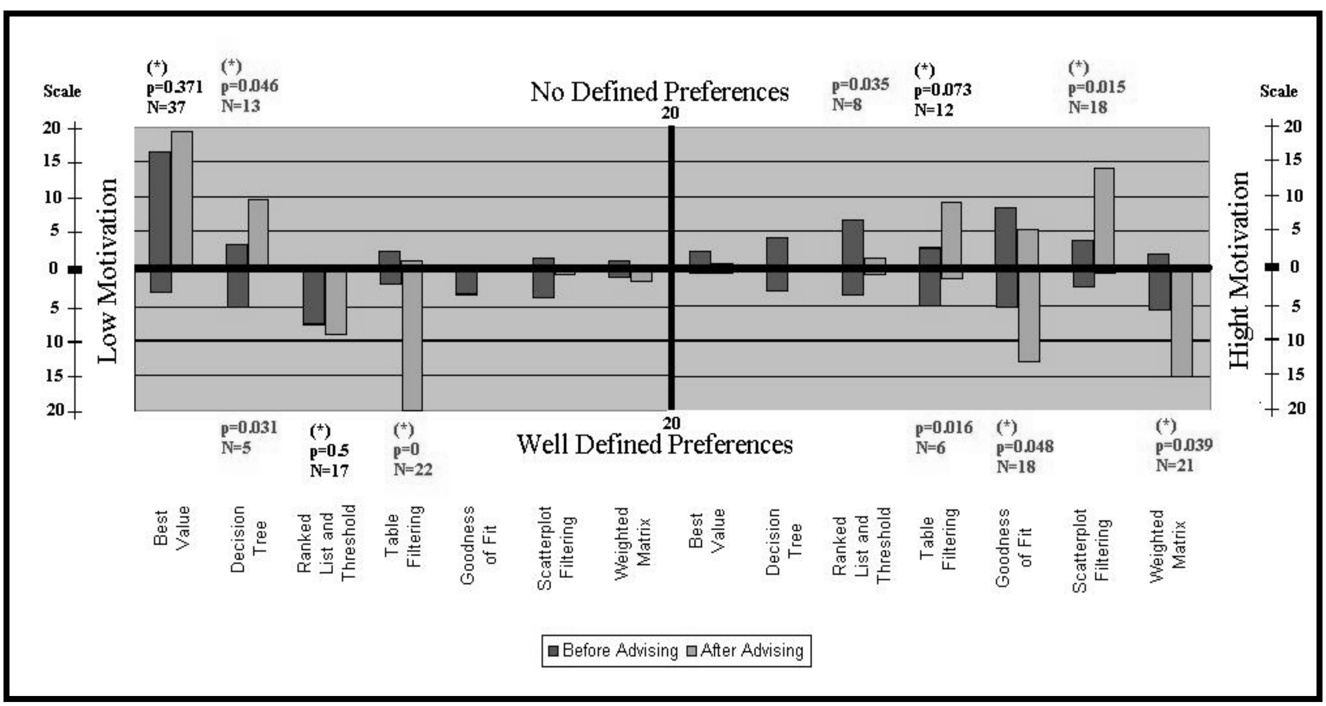

Figure 10: Decision Tool Selection in Four Different Scenarios

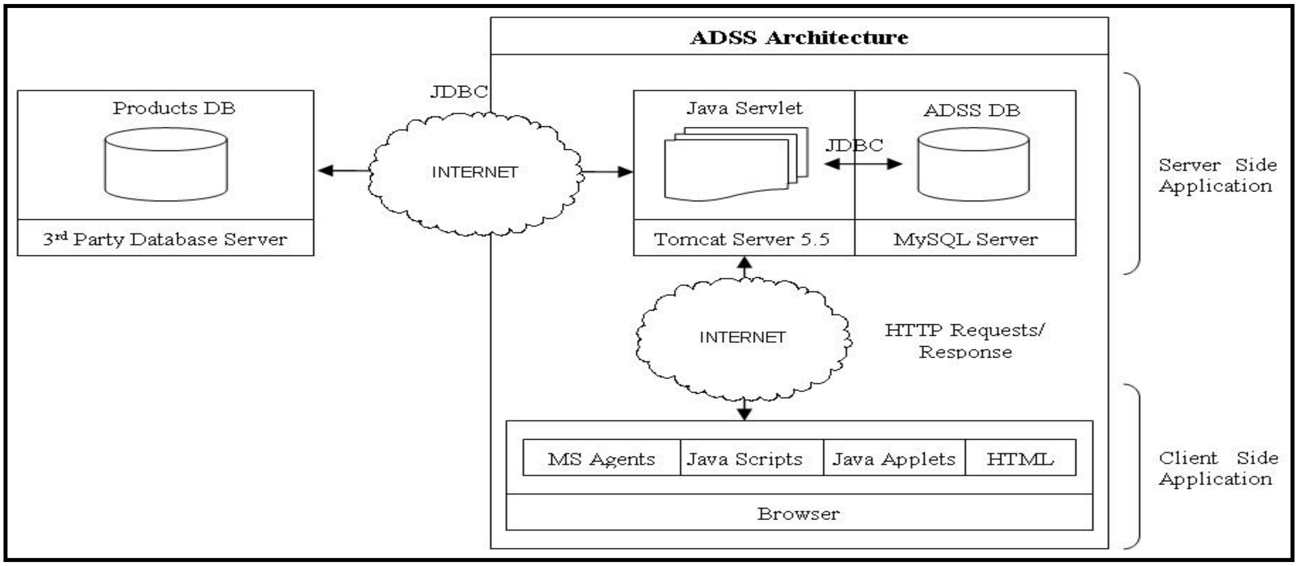

Figure 11: ADSS High-Level Architecture

after advising where Weighted Matrix and Goodness-of-Fit were recommended, subjects changed their ratings to follow the system recommendation. The effects of advice on Weighted Matrix and Table Filtering were significant (p=0.039 and p=0.016 respectively).

4.4 Conclusion

Experiment results showed clearly that subjects changed their preferences to the system-recommended tools (the null hypothesis is rejected because the data showed a significant difference between the two categories for most tools in different scenarios). This shows that the effect of a social actor in delivering the system advice is effective and persuasive. In addition, the results showed that subjects responded to the system advice differently in each scenario. As a consequence, different levels of advice should be provided to the users in different scenarios to satisfy their requirements. The decision tools selected by the subjects in each scenario imply that they prefer a particular decision tool according to the scenarios' requirements. These different decision tools and advice could support users in making their decision more effectively.

5. ADSS ARCHITECTURE AND PROTOTYPE

The ADSS assists users by guiding and advising them to use appropriate decision tools, decision strategies, domain advice, etc., that are likely to improve their decision. Since the requirement study results showed that the subjects needed for different decision tools that allow them to perform different decision strategies, six decision tools were implemented in the first prototype of ADSS. In addition, the study results showed that the effect of a social actor (Wizard of Oz) in delivering advice was effective and persuasive. As a result, a MS-Agent was used to represent the system advisor to deliver different types of advice and recommend which tool to use according to the scenarios' requirements and the task domain.

The followings sections describe the design of the ADSS system and its architecture.

5.1 High Level System Architecture

As shown in Figure 11, three-tier client-server architecture was chosen. The aim of the ADSS design is to develop a generic configurable software technology that can be integrated with any third party E-Commerce system to support consumers in search and choice processes of online shopping.

An Object-Oriented modeling approach was used for the server-side programs, uniformly representing classes and relationships of users, products' domains, system advisor, and decision tools as well as data, model and knowledge. In addition, the server-side is responsible for serving the client side by processing complex computational tasks and making any necessary calls to retrieve data from the ADSS database and/or from any third party product databases that may be located on different servers.

The database design for ADSS can be configured to be integrated with any decision tools, product domains and the advisor rules and advice.

The client-side programs are responsible for running the decision tools that use different forms of visual displays, managing the users' interactions with the system, and delivering system advice to the user. In addition, they retrieve necessary data by calling appropriate server-side programs which in turn may require calling the ADSS database located on the database's server.

5.2 System Implementation

Several technologies were used to implement the system. The first technology used is the Java Servlet language which is responsible for creating the server-side embedded class models, running on Tomcat Server 5.5. The MySQL server 4.1 was used to build the system database structure.

On the client side, Java applets produce different forms of visual displays (e.g. scatterplot and decision tree displays) because of their ability to use any Java packages and APIs. Secondly, Java Script was used to generate dynamic HTML and interacts with Java applets and MS agents' ActiveX. MS Agents version 2.0 is used to deliver the system advice to the users.

5.3 ADSS Prototype

An early prototype of the system using the proposed ADSS framework with six decision tools has been implemented. This prototype is configured to be used with a Student Accommodation database to support students at Manchester in making their decision on which accommodation to choose.

Initially the user logs on to the system and answers questions related to their level of motivation and preferences and the intended product domain which enable the system to build an initial user model and retrieve the product model of the selected domain. The system uses these models and the decision rules from the system advisor to recommend appropriate decision tools for the user. The recommended tools are highlighted and the advice is delivered using MS Agent as shown in Figure 8. The user may select any tool from the list and then run the selected tool. Figures 3 to 7 show examples of the decision tools implemented in the first prototype of ADSS.

5.4 Scenarios of Use of the Decision Tools

Table 2 summarizes scenarios of use of the decision tools and examples of each decision tool support.

Table 2: Decision Tools Scenarios of Use

Tool Name	Motivation	Defined Preferences	Tool Support Examples
Concept Map	Low or Moderate	No or Partially	Exploration and use of pre-defined queries.
Scatterplot Filtering	High or Moderate	No or Partially	Exploration, Dynamic filtering
Decision Tree	Low or Moderate	No or Partially	Guide users through pre-defined queries in hierarchical tree
Ranked List	High or Moderate	Partially or Well	Thresholds filtering using range sliders
Goodness of Fit	High	Well	Allow Partial Match and trade-offs using weights
Best-Value	Low	No or few	Displays Small subset of best value choices

6. CONCLUSION AND FUTURE WORK

This paper presented a novel concept of ADSS using a combination of decision tools and advice dialogues to support E-Commerce consumers in their decision making process. In addition, a preliminary requirements investigation has been described which used an adapted Wizard of Oz approach to test users' reaction to mock-ups of the ADSS with and without system advice. The requirements study tested users' reaction to the proposed tools and showed how they were influenced by the system advice.

This paper concludes that the use of a social actor in delivering system advice is effective and persuasive. In addition, different decision tools are needed for users to allow them to perform their decision strategies in different scenarios and product domains. Furthermore, different levels of advice are required by the users in different scenarios to satisfy their requirements and improve their decision. These different decision tools and advice could support users in making their decision more effectively. These findings provide practical requirements for future design of B2C E-Commerce ADSS. Finally, the paper described briefly the system architecture, design and prototype implementation with six decision tools.

The next step is to evaluate the system in usability experiments to explore the user requirements, problems and difficulties, as well as test the users' reactions toward the system advice with a social actor in different scenarios and product domains. Consequently, the results of this experiment will be used to revise and extend the theoretical framework and the system design.

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