A Decision Support System for Infrequent Purchase Decisions in E-Commerce

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Abstract

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In this paper, we propose an approach for supporting e-commerce buyers who do not have clear goals and well-defined preferences regarding the products of purchase. This is particularly the case when the purchase of such products is infrequent, e.g. home theaters and laptop computers. Our method allows customers to express vague preferences and dynamically gives advisory information without limiting customer's opportunity to consider all possible solutions. The system is based on fuzzy logic algorithm, cluster analysis, and the well-known "divergence/convergence" principle from problem solving research. The results of an experiment with the prototype systems are in favor of our proposed methods compared to traditional catalog method.

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1 Introduction

A large number of consumers use World Wide Web to obtain product information before purchase (Detlor et. al. 2003; Haubl and Trifts 2000, Phau and Poon 2000; Alba et al. 1997). Modern technologies have greatly enhanced e-commerce customer's ability to acquire and process product and merchant- related information to make more favorable shopping decisions; interest in this topic has been fueled by the observation that e-commerce is empowering modern customers in unprecedented ways (McDonald, J. and Tobin, J, 1998). At the same time, customers are overwhelmed and challenged by the humongous amount of information that is available to them. Therefore, it is essential to design information systems or tools to facilitate customers' decision processes and optimize their decision outcomes. "The digital retailing practice has to embrace the broad approach to the opportunities offered by an interactive medium that attracts many millions of potential buyers" (Zwass, 1999). This value-added service that could solve complex customer problems by offering interactive search methods and comprehensive advisory system is of significant importance to the success of e-commerce malls (Schumann, Horstmann, and Mertens; 2000). A recent research on online customer behavior found that value-added search mechanisms in web-based stores with decision support capacity were positively related to customer's shopping enjoyment and hence better customer retention (Koufaris, 2002). Another study suggests that the online shopping environment should allow a full spectrum of pre-purchase information seeking activities, i.e. from browsing to searching; in addition, certain information such as retailer advice, retailer selection, product description, etc. should be displayed for both browsing and searching activities (Detlor, Sproule, and Gupta; 2003).

The motivation of our study is customers' need for decision support systems that would help effectively analyze product information in the presence of a large number of product alternatives. This is especially important when the customer is relatively unfamiliar about the product and is not sure about the exact product features that s/he is looking for. In such case, much complexity and confusion may exist throughout the selection process while customer is evaluating the trade-offs between the price and other product attributes. Supporting systems or tools are needed to sort out the available information in a way that customers can make better decisions.

Our target of study is e-commerce customers who do not have clear goals and well-defined preferences about the products of purchase. This is particularly the case when the purchase of such products is infrequent, for example, home theaters, laptop computers, furniture, and etc. (Lee et al., 2002). From the problem-solving point of view, infrequent shopping suits well into the category of ill-structured problem because the objectives in the shopping tasks are unclear. For generating ideal solutions for such problems, we will need Decision Support System (DSS).

The importance of applying decision support systems (DSS) in e-commerce websites has been widely addressed (Miles et al., 2000; Silverman et al., 2001). The increasing application of DSS for e-commerce customers has brought up the notion of "caveat mercator" or "seller beware". Because with supporting systems, buyers can now be more efficient in analyzing product- and merchant- related information and consequently optimize their decision-making (Convay and Koehler, 2000). Our goal in this study is to develop active DSS for shopping support that would allow customers to express vague preferences and dynamically give advisory information without limiting customer's opportunity to consider all possible solutions. To accomplish that, we employed fuzzy logic algorithm, cluster analysis, and the well-known "divergence/convergence" principle from problem solving research.

The paper starts with the literature reviews on Consumer Buying Behavior model and its implications on e-commerce buyer support, followed by the discussion of the existing decision support techniques in e-commerce and how they enhance e-commerce customer's decision making. Thereafter, we will propose our approach of supporting buyers of infrequently-purchased products, explain our prototype systems for notebook computer selection, and finally discuss the results of the evaluation experiment. The paper concludes with brief summary and suggestions for future research.

2 Background

2.1 Consumer Buying Behavior (CBB) Models and Buyer Profiles

Coming from traditional marketing research, Consumer Buying Behavior (CBB) model presents a useful tool to understand the activities in e-Commerce (Guttman et al., 1998; Miles et al., 2000). Different versions of CBB model have been widely used in research for e-commerce buyer support (Miles et al., 2000; Silverman et al., 2001, Guttman et al., 1998; O'Keefe and McEachern, 1998).

Guttman et al. (1998) suggested six stages of consumer behavior that e-commerce systems should be supporting on: 1) need identification (the consumer identifies the need for a product); 2) product brokering (the consumer identifies products that can satisfy the need); 3) merchant brokering (the consumer decides the seller of the product); 4) negotiation (the customer and the seller negotiate over the terms of the transaction); 5) purchase and delivery; 6) after purchase evaluation. O'Keefe and McEachern (1998), on the other hand, proposed five decision-making activities: a) need recognition, b) information search, c) evaluation, d) purchase, and e) after purchase evaluation.

Based on Guttman et al.'s model and O'Keefe and McEachern's model, Miles, Howes, and Davis (2000) focused on the early stages of decision-making processes in e-commerce shopping that have more psychological demands on consumers: 1) search for products, 2) management of search criteria, and 3) comparison of found products.

Moreover, these three stages, Miles et al. argued, corresponded respectively to the Simon's classical three-phase decision-making processes from traditional DSS literature: design, intelligence and choice, wherein *design* refers to finding alternative solutions, *intelligence* to finding useful information, and *choice* to selecting among alternatives. In this regard, viewing e-commerce systems as decision support systems, Miles et al. surveyed 13 alternative types of websites that have searching, browsing, and/or product comparison capabilities. Based on the results of the survey, a theoretical framework was developed to guide the interface design for e-customer's buying decision making support.

Building on Miles et al.'s work, Nah and Davis (2002) suggested that e-commerce sites' *searching* capability is more suitable for the customers who have a clear idea of what they are looking for, while *browsing* (or navigation) capability seems to fit customers who do not have such well-defined goals. This is in line with the Task Fit Theory (TFT), which suggests that information systems have a positive influence on the user performance only when the functionality of the system fits the user's task requirements (Goodhue 1998, 1995, 1988; Goodhue and Thompson, 1995).

E-commerce researchers have stressed the importance of distinguishing two modes of information seeking in online or traditional customer buying behaviors: *browsing* and *searching* (Rowley, 2000; Toms, 2000; Nah and Davis, 2002; Detlor et al., 2003). *Browsing* (or navigation, surfing, information discovery, information exploration) is "an activity in which one gathers information while scanning an information space without an explicit objective" (Toms 2000, pp .424). It happens when the consumer does not have a well-defined goal towards what exactly he or she is looking for, and therefore the process may sometimes be experimental, random, and unpredictable. *Searching* (or directed search), on the other hand, requires explicit objectives and is goal-directed behavior (Nah and Davis, 2002; Detlor et al., 2003). Detlor et al. (2003) advocated that the commercial e-commerce websites should be able to support both types of information seeking activities.

To better understand buyer decision process, marketing researchers have long realized the importance to identify different buyer profiles. Based on buyer's prior product knowledge, buyers can be categorized into low-knowledge, moderate-knowledge, and high-knowledge buyers. The low-knowledge buyers depend on holistic information processing rather than analytic processing, and they tend to make similarity-based inferences (Alba and Hutchinson, 1987). Moderate-knowledge buyers, on the other hand, are adequately familiar with product attributes and are able to examine detailed functional attribute data (Smith and Wortzel, 1997). Their capability to assess and analyze complex attribute data is similar to that of high-knowledge buyers (Rao and Monroe, 1998). Finally, high-knowledge buyers possess highly comprehensive knowledge of the product category, brands, and attributes, and they are able to process attribute and brand information spontaneously (Alba and Hutchinson, 1987). In this study, we focus on the infrequently-purchased products and their customers, who are unfamiliar with the product, their product knowledge is limited, and hence belong to the low-knowledge buyers' category. Moreover, the tendency to use similarity-based inferences by low-knowledge buyers should also be incorporated for their decision support.

Buyer prior knowledge about the product significantly affects the way customers process product information and make choices. Experts are more likely to *deduct* when it comes to information gathering and problems solving, while novices (or non-experts) *induct*. To be more specific, experts tend to spend more effort on identifying and defining the problem as if "formulating hypotheses and then test these by acquiring relevant information"; the non-experts, on the contrary, would "... explore information to look for *differences* and generate propositions. Thus they initially appear to have only *vague* ideas about what they want." (Selnes and Troye, 1989 pp. 425) Therefore, to effectively support novice customers, the system has to take into account their inductive behavior in framing the problem. In doing so, the system should allow and be able to understand their vague ideas and initiatives, help comparing the product differences as well as trade-offs, and present best propositions with all possibilities.

2.2 DSS in E-Commerce

The importance of applying decision support systems (DSS) in e-commerce websites has been widely addressed (Miles et al., 2000; Silverman et al., 2001) A decision support system (DSS) is "an interactive information system that provides information, models and data manipulation tools to help make decisions in semi-structured and unstructured situations where no one knows exactly how the decision should be made." (Silverman et al., 2001 pp.818) The traditional DSS method includes use of models, interactive problem-solving, user-controlled analyzing data and evaluating decision alternatives (Silverman et al., 2001).

Silverman et al. identified three levels of DSS in e-commerce shopping websites: access focused, transaction focused, and relationship focused. The first level websites only offer simple user-pulled information access, such as basic search and browsing capabilities; the second level websites interactively offer more support for buyer's mental processes, e.g. provide default settings and templates, guided choices, and well-structured steps; the third level websites focus on maintaining long term relationship with the customers and are similar to Customer Relationship Management (CRM) systems. Our focus in this paper is on the second level of DSS because we primarily aim to support and improve customer's buying process and outcomes.

2.3 DSS for Infrequent Purchase vs. Frequent Purchase

As we discussed earlier, the basic support that a website could offer is search and browsing capabilities. But in the case of directed search, customers have to have a clear idea about what they are looking for, e.g. exact product features, specific vendors, etc. In the case of browsing, when customers do not have such a clear goal, they will have to look through a set of product alternatives – the size of the set has to be reasonably small to avoid the problem of information overloading; or, a more advanced active type of support, recommendation systems (Stohr, 1999), seem to help with the situation.

Lee et al. (2002) build personalized, agent-based recommender systems for both frequent purchase and infrequent purchase products. Notably, Lee et al. distinguished frequent (regular) purchase and infrequent purchase as two types of shopping tasks and treated them differently in the recommender system design. For frequently purchased items, e.g. CDs, books, the system learns the customers' personal preferences from their historical activities or purchases (i.e. customer profiles) from the website, and thus to make personalized purchase recommendations. While for the infrequently purchased products or services, e.g. notebook computers and home theatre systems, the historical data are not available, the recommender system will have to solicit customers' current preferences through an interactive fashion.

2.4 Methods to Model Customer's Preferences

Different techniques have been used to model customer preferences. Lee et al. (2002) used the *common model-based approach* (i.e. using a vector of weights, each of which represents the relative importance of a given attribute to the customer) in their agent-based recommender system for DVDs. Moreover, *Genetic Algorithm* is used in Lee et al.'s system to learn about customer's preferences; the accuracy of the model, which is measured by the error of prediction (i.e. the difference between the preference prediction and actual preference given by the customer), is improved over time in the "evolutionary mechanism" (Lee et al., 2002 pp. 279). Similarly, Pazzani and Billsus (2002) used the vector of weights to model preferences for the source of document recommendation in their adaptive website agents; the agent system increases (or decrease) the weight by a constant factor so as to adapt the user's preferences when the recommendation is accepted (or not accepted.)

Conjoint Analysis is a method widely used in marketing research to solicit customer preferences for product positioning and pricing; it collects customer utilities and perceived importance of different product attributes, estimates customer value system, and predicts customer purchasing choices (Curry, 1996). In conjoint analysis, customer is asked to rank different product items and feature combinations with respect to their desirability and importance. From these collected customer preferences, Utility models are formed. Thereafter, these models are used to rank new set of products and predict future purchases. A sample of Conjoint Analysis can be found at Active Decisions – "Active Sales Assistant" (http://activebuyersguide.com/), which helps select a product from a number of categories. In addition, computer-based interviewing technique has been used to enhance conjoint analysis, and this enhanced technique is sometimes called "*Adaptive Conjoint Analysis*" (*ACA*). In the computer-administered approach, customers are asked a series of questions, each of which depends on the answers to previous questions that the customer gave the system. As such, in an adaptive fashion, interviewing questions are customized or optimized for individual customers so that only the most relevant questions are asked (Huber, 1987).

Different techniques from *Artificial Intelligence* (*AI*) are also employed for modeling preferences and product recommendations. Prasad (2003) categorized AI applications for e-Commerce into three classes: AI systems for B2B e-commerce, for B2C e-Commerce, and for both B2B and B2C e-Commerce. *Knowledge based approach* is widely used in the category of AI systems for B2C e-Commerce. Examples of knowledge-based recommender systems include "Exsys Corvid" (http://www.exsys.com/) and "DecisionScript" (http://www.vanguardsw.com/decisionscript/); for instance, the Exsys site features demos on camcorder selection and restaurant recommendation. To catch customer's preferences and make product recommendations, most knowledge based approaches either incorporate CBR (Case Based Reasoning) or *GBR (Goal Based Retrieval)* (Prasad, 2003). To be specific, CBR learns from past experiences or customer profiles to make recommendations in terms of product similarity. For example, Yager (1997) has proposed a fuzzy logic-based multi-agent system for real-time advertising selection based on customer profiles. Additionally, Nearest Neighbor Retrieval technique coupled with weighted Euclidean distance is usually used in CBR to quantify product similarities (Prasad, 2003). GBR, on the other hand, would recommend related products for a similar shopping goal a customer may have (e.g. an umbrella and a raincoat.) (Prasad, 2003). Another alternative knowledge based approach is the *inductive technique*. For example, Kim et al. (2001) build a personalized advertisement system for Internet Storefronts which uses data-mined customer demographic information to match product categories.

Another popular approach of recommender systems is *collaborative filtering* or *ACF (Automated Collaborative Filtering)*. (Prasad, 2003; Guttman et al., 1998; Sarwar et al., 2000; Schafer et al., 2001). It is sometimes referred to as the "word-of-the-mouth" approach because it recommends the opinions from like-minded people. The techniques to measure similarity, such as cluster analysis and nearest neighbor, are usually used by these systems. An example of ACF system would be http://movielens.umn.edu/ for movie recommendations, where 'neighborhoods' of similar-minded people are formed by calculating the correlations of their tastes (i.e. their ratings towards commonly seen movies), and then the ratings towards new movies from these neighbors are used to generate recommendations for the target member.

Software agents, the software components with features of autonomy, reactivity, proactiveness, and social ability (Wooldridge and Jennings, 1995), are often incorporated in the buying support systems (Guttman et al., 1998; Karacapilidis and Moraitis, 2001; Maes et al., 1999). They are employed to support different shopping stages in the CBB model, specifically in the stages of product brokering, merchant brokering, and negotiation (Guttman et al., 1998; Pedersen, 2000). The importance of software agents in decision support for e-commerce has been well-emphasized and documented in the special issues (Liang, 2000) and the special section (Blake and Gini, 2002) in International Journal of Electronic Commerce and the two special issues in Decision Support Systems Journal (Whinston, 1997; Yen, 2000). From e-commerce support perspective, the agent's features of autonomy and proactiveness would help to reduce cognitive burdens on e-commerce customers. Therefore, we favor the active nature of support in the system design for informing customers' shopping process.

3 A Framework for Decision Support for Infrequent Purchases

Based on the review of previous work on supporting technologies in e-Commerce, Decision Support Systems, and Consumer Buying Model from marketing research, we have developed a framework with two dimensions: *frequency of purchase* and *system proactiveness*. The framework is an attempt to categorize past work and analyze the key similarities and differences among reviewed technologies.

Frequency of the purchase relates to the "structuredness" of the shopping task, and therefore determines the kind of support required in the task. In frequent shopping scenarios, the customers have relatively well-defined goals and preferences; while in infrequent shopping, the customers are usually unclear about their shopping objectives and preferences. This is corresponding to the comparison between ill-structured tasks and well-structured ones. The objectives are likely to be unclear if the tasks are ill-structured, while relatively well-defined in well-structured tasks (MacCrimmon and Taylor, 1976). Therefore, infrequent shopping tends to be ill-structured task, which has traditionally been researched in the domain of Decision Support Systems (Keen and Morton, 1978; Stabell, 1994).

System proactiveness relates to the recent trends in DSS research on the design for active systems (Angehrn, 1993; Carlsson et al., 1999; Fazlollahi and Vahidov, 2001; Manheim, 1988; Vahidov, 2002). The advocates of active DSS suggested that DSS systems should be more active as to take initiatives to make certain decisions on behalf of their users, while the passive nature of traditional "toolbox" type of DSS would not be able to do so. Moreover, Angehrn (1993) suggested that the ideal DSS would entail the interaction between the system and the user, where both parties should be active.

Table 1 illustrates the proposed framework and how the past technologies can be described with this framework. The two abovementioned dimensions outline four quadrants, according to the frequency of purchase in the shopping tasks and the degree of proactiveness in the decision support systems.

Table 1 Summary of buyer support methods

Shopping \ Support	Passive	Active
Frequent	Electronic catalog Basic search & browse	Recommendation systems, software agents
Infrequent	Browse, basic & advanced search, comparison shopping	Active DSS for shopping support

The frequent shopping and passive support quadrant includes traditional electronic catalog with basic search and browsing capabilities. On top of the basics, the infrequent shopping and passive support added advanced search and comparison shopping mechanisms. Moreover, various recommendation systems and software agents fit in the frequent shopping and active support quadrant. However, no attempt has been made for the most advanced quadrant, i.e. the infrequent shopping and active support. Our aim is to develop active DSS for shopping support that would elicit customer preferences and give advisory information.

Many e-business systems nowadays with active support systems would try to gather information from customers and then automatically recommend a list of items together with ranking, e.g. Amazon.com. The underlying technical methods are usually collaborative filtering, conjoint analysis, etc. We place this kind of systems in the frequent shopping and active support quadrant. Because to make personalized recommendations based on customers' persistent or semi-persistent preferences, the system would have to possess certain information of the customers from their historical transactions or visits on the website, and for that reason, the shopping tasks are tend to be regular or frequent.

However, in the infrequent shopping scenarios, it is not appropriate to elicit "exact" preferences or utilities, because the customer may simply not have well-defined preferences or precise goals yet; even worse, collecting such preferences may also lead to overlooking different alternatives that customer would consider otherwise.

Infrequent shopping suits well into the category of ill-structured problem solving, because the objectives in the shopping tasks are unclear. For this kind of shopping, customers usually have to use basic browsing and exploratory search to learn and understand more about the product and then gradually form their preferences of the product. For this reason, browsing, as a discovery or experimental pre-purchase information gathering, may be more suitable here in infrequent shopping (Nah and Davis, 2002). Searching tools for this kind of tasks should also be more "value-added" than those in frequent shopping scenarios. Lee et al. (2002) proposed a personalized recommendation system which uses "performance" of product functional features instead of using functional features or technical parameter. It is because the infrequent shoppers, usually the novices of the products, may not understand the latter. For example, users would assess with the term "the performance of CPU" much better than the "type and processor frequency of CPU" (Lee et al., 2002). This value-added search incorporates many-to-many database mapping between the functional features and performance of the functionality. When users change their preferences and weights on the product characteristics, the system will adapt to the changes iteratively and re-generate a list of top ten recommendations.

This approach is very much inline with the "means-end" chain model in marketing research, although Lee et al. (2002) did not link their work with the model. Subramony (2002) empirically proved the model's applicability in the human-computer interactions for web browsing activities. The essence of "means-end" model is a "ladder" structure that connecting to higher and higher levels of knowledge abstraction: from the product "attributes" to the abstract "consequences" of the consumptions of those specific attributes, and then to the more abstract personal "values" linked to those consequences

(Bagozzi and Dabholkar, 1994; Gutman, 1982). In other words, product attributes are a means for some desired consequences; consequences are a means to attain certain personal goals, values, or "a desired end state of existence", such as security (Subramony, 2002 pp. 145). A simple example of such means-end association would be: the attribute "self-timer" of a camera leads to the consequence/benefit of "I can be in my own pictures" (Graeff, 1997 pp.165), and therefore maybe "I can picture my life" (personal value). Thus, by using means-end references, customers are able to form an integrated understanding of the product, from means to ends, cause to effect (Graeff, 1997).

Subramony (2002) applied the means-end model to understand the relationships between websites and their users, and found that the reason why people would prefer certain websites over the others depends on whether or not they can find personal relevance from the physical website attributes, or in essence, whether or not they can form the attribute-consequence-value connection. From this regard, we would say that Lee et al. (2002)'s work is an attempt to integrate the "consequences" of certain product "attributes" to the value-added search in their proposed systems.

Moreover, the means-end chain inferences are significantly affected by customer's product knowledge. Comparing to the experts, novices are less likely to use means-end inferences in the product comprehension because they lack the necessary product knowledge to form the cause-and-effect or means-end connections between product attributes and the associated consequences (Graeff, 1997). On the other hand, as a part of product comprehension, forming these personally relevant consequences will directly affect customer's ability to evaluate the product attributes, because customer's evaluation is based on the given product information as well as its inferred personal meanings or beliefs (Graeff, 1997). Novice customers, with limited means-end product knowledge, lacking the ability to form personally relevant consequences, are less able to evaluate product attributes. Maheswaran and Sternthal (1990) also suggested that novice customers are more motivated to process product information when given benefit information, or both product attributes and benefit information; while expert customers are more motivated by attributes-only type of information. Therefore, to effectively support novice customers, the DSS should help form the means-end connections by presenting the product consequences or both the attributes and the consequences. One way of doing so is to incorporate adequate glossary module into DSS which explains the product attributes with their consequences and benefits.

Our work focuses on the "infrequent/active" quadrant, and we agree with Angehrn (1993)'s view of ideal DSS, i.e. both the system and the user should be active in interaction. In this regard, Pu et al. (2003) promoted interactive, incremental, and flexible user preference elicitation where certain inconsistencies in user's preferences should be tolerated. The constraint satisfaction problem-solving was used in their system to generate recommendation list and to revise user preference model. Moreover, Pu et al. proposed a list of system design principles that would better grasp users' utilities by helping them manage their fundamental objectives, hidden preferences and conflicting preferences. Four travel-planning systems, ClubMed.com, VacationPlanner, SmartClient-Travel, and Isy-Travel, were used to demonstrate these design principles (Pu et al., 2003).

We concur with Pu et al.'s view on system's flexibility and tolerance on user preference elicitation. In this respect, we argue that incorporating Fuzzy Set Theory and Fuzzy Arithmetic could improve user preference model because it expands the system's capability to grasp users' imprecise expression of their utilities. The system with fuzzy preference model would be able to fully reflect the level of vagueness in user's utilities and determine the set of relevant product alternatives according to the "soft" preference model. In the case of infrequent shopping, such technique has to be combined with the principles of problem solving and ill-structured problem decision-making. In the following section, we will explain the principles of problem-solving and their applications in buying decision support.

4 Decision Support and Problem Solving

Problem solving is very close to decision making; some researchers do not even distinguish the two (MacCrimmon and Taylor, 1976). Solving a problem involves a series of transformations from the problem's initial state to the preferred state. Different researchers have different understanding or description towards this process of transformation (Lev, 2002). When any of these states or the relevant transformations is not well-defined, the problem is ill-structured. In this study, we specifically investigate the ill-structured infrequent shopping activities where the buyers do not know how to clearly define what they are looking for.

The main principle we propose in this work for solving ill-structured problem is to apply divergent and convergent thinking along the processes of problem solving. Divergent thinking is for idea generation, while convergent thinking for alternative evaluation. Evans (1990) suggested that the system for problem solving should have the capability to produce diverse alternatives, if possible, in a single run. He also supported his view with Woolsey's comment "When you give the manager a spread of alternatives, with good points and bad points outlined, few can argue that the work is insufficient". Although divergent and convergent thinking can be applied throughout all stages in problem solving, the divergent thinking activities are more important in the earlier stages, while the convergent ones in the later stages (Basadur, 1994).

The principle of divergent approaches has been used together with genetic algorithms (Fazlollahi and Vahidov, 2001) and agent technology (Vahidov, 2002) for alternative generation in DSSs. In this work, we propose a DSS that is consistent with the logic discussed above: the system will first identify the set of qualifying products, then it will present more dissimilar product alternatives in the beginning of browsing while more similar ones towards the end. In other words, within the set of desired products, the system presents the most diverse product alternatives in the beginning of the browsing process. Once the user chooses to explore one of these products, the neighborhood of that product becomes the next set of qualifying products, and the most diverse product alternatives within this set will be presented; at this point, the diversity / dissimilarity of these presented products will be smaller than that of the previous step or the starting point. In this process, users actually "zoom into" the preferred neighborhood of products. With this process going on for a few steps, users will narrow down and focus on the products that are more and more similar and specific in their key attributes. Also, users can "zoom out" of the neighborhood anytime during the browsing process and look at other neighborhoods. They may also go back to reset or modify their preferences, and they can stop browsing neighborhoods of products but rather investigate the detailed information of any individual product item that interests them. In general, the divergence is more important in the earlier phases (for idea generation) while the convergence is in the later phases (for alternative evaluation). Figure 1 shows the logic.

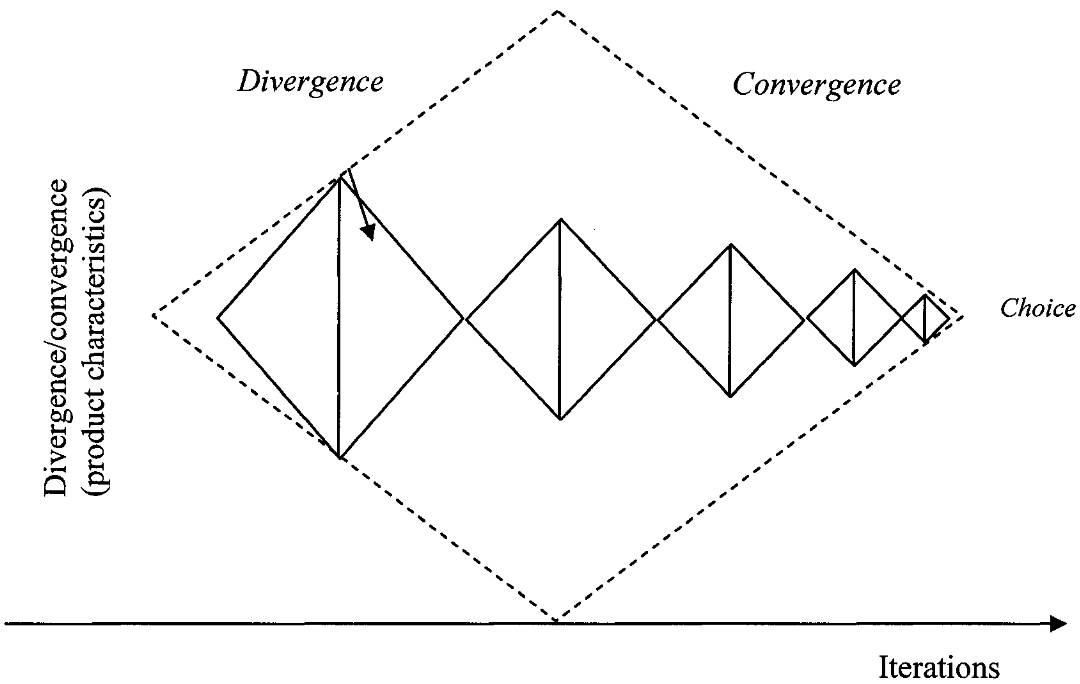

Figure 1. Divergent and convergent processes in product selection decision

The symbols of divergence and convergence are from the creative problem solving literature (Basadur, 1994). We can see that, at each step, user browses the divergent product alternatives and converges on one of them. This convergence then creates a new set of less divergent alternatives. This process continues till the end of convergence. The process may not be linear; users may stop and make final choice early in the process, or they may iterate the process backward and forward throughout the browsing process. Overall, the figure depicts the main logic of the alternative generation and divergent / convergent browsing processes.

This divergent and convergent process can also be related to the anchoring and adjustment theory in marketing (Tversky and Kahnemen, 1974), which suggests that people evaluate and make heuristic decisions in relation to anchor points or reference points to lessen their cognitive effort and decision processing. This theory is often applied in advertisement in favor of the merchants; anchor points suggested by the ads mostly lead and limit customers to chose specific products/services or other decisions to the advantage of the sellers. We on the contrary apply this theory in support of the buyers, so that the system would help reduce cognitive overload while at the same time help buyers find their optimal solutions. Therefore, in line with this theory and also not to limit customer's choices, our system will present diverse reference/anchor points in the beginning (i.e. the most divergent product alternatives which represent the most diverse product categories) and then allow adjustment making throughout the process according to customer's interests (i.e. zoom in the neighborhood for similar offers). Furthermore, multiple diverse reference points, which suggest all available solutions, should also bring up the level of trust from customers, since single reference point can often be perceived as manipulation.

5 Method for Buyer Decision Support

Our decision support system incorporates both browsing and searching capabilities because both experiential and goal-directed searching behaviors are important in supporting buyers' shopping processes. Our system contains two basic modules: the module for identifying the set of promising alternative products and the module for generating divergent product suggestions. In the first module, the system identifies the set of most desired products according to the product attributes and the preferences that were imprecisely specified by the customer. This step narrows down the number of products that customers need to look at and helps reduce cognitive overload problems. In the second module, within the above identified sets, the system interactively generates divergent offerings to the customer, and this is done by following the divergence/convergence principle of problem-solving discussed earlier. We will discuss these two modules in more details in the following sections.

5.1 Identifying the Set of Promising Alternative Products

Fuzzy logic and fuzzy sets provide a simple and intuitive way to describe and model vague or ambiguous input information, such as customer preferences (Kaufmann and Gupta, 1985; Klir and Yuan, 1995). In our system, we use fuzzy sets to capture the relative importance that customer put on each product attributes, e.g. price, brand name, etc. Moreover, we employ a linear model to calculate the overall utility or the attractiveness of a particular candidate product:

$$\widetilde{U}^a = \sum_{i=1}^{n} \widetilde{u}_i^a \cdot \widetilde{w}_i \tag{1}$$

In this formula, $\widetilde{U}^a$ symbolizes the overall fuzzy utility' $\widetilde{u}_i^a$ stands for the utility of the i^{th} attribute of the product, and $\widetilde{w}_i$ indicates a fuzzy weight of that attribute. Similar fuzzy multi-attribute methods for decision support systems have been proposed and evaluated in the past (Trantaphyllou and Lin, 1999). We use fuzzy values to allow customers to imprecisely define the importance (or the weights) of the product attributes. Some attributes of the product, e.g. memory, screen size, etc. are naturally crisp in value, but certain other attributes can also be represented fuzzily, e.g. the reputation of the manufacturer, the reputation of the brand name, etc. For simplicity, we treat all the utilities of individual attributes as crisp utilities. However, we stress on allowing and capturing the fuzzy expression of the importance that customers give on those product attributes.

Fuzzy sets are characterized by the membership function, which uses the membership value (a value in the unit interval [0, 1]) to describe the degree of membership of an element/member. For example, the membership value 0 means that the element does not belong to the given fuzzy set; while the membership value 1 means that the element is fully included in the given fuzzy set; any membership value that is between 0 and 1 describes the degree of fuzziness of a given member (Trantaphyllou and Lin, 1999). The degree of membership of a member x to a fuzzy set a is denoted as $\mu_a(x)$. The fuzzy set can be denoted as interval S such that $S_a = \{x \mid \mu_a(x) > 0\}$.

A fuzzy number can be defined by a fuzzy set of ordinary single-valued numbers that each one of them has a membership value associated with it. The membership functions of fuzzy numbers are usually convex, and if plotted on a rectangular coordinate, some of the most popular plot shapes would be triangular, trapezoidal, and bell-curved[1]. For the reason of simplicity, we use the triangular shape for depicting fuzzy numbers. The examples of triangular fuzzy numbers are shown in Figure 2. We can see that a fuzzy number is depicted by three points on the real-number scale. For example, fuzzy number a can be given by (7, 0), (1, 10), and (13, 0). (7, 13) is the support of fuzzy number a, with the peak value 10. We can interpret a as "around 10", and the single-valued number "10" has full membership of 1; the further away from the peak value 10 a single-valued number gets, the smaller membership it would have. Therefore, the single-valued number 7 barely has the membership or can hardly be considered as "around 10", the same goes to 13. Fuzzy numbers do not have to have symmetric membership functions, and the shape of the membership curve can be concave or irregular[2].

[1] http://whatis.techtarget.com/definition/0,,sid9_gci283979,00.html
[2] http://whatis.techtarget.com/definition/0,,sid9_gci283979,00.html

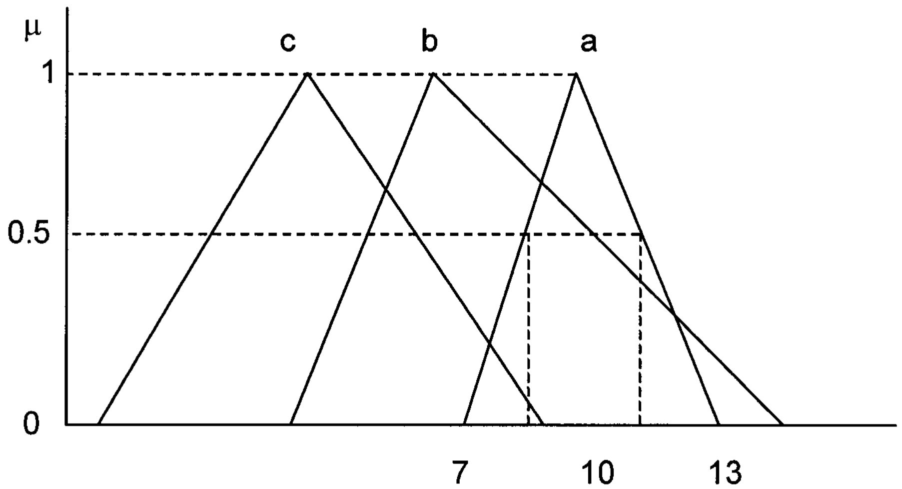

Figure 2 Fuzzy numbers

Alpha-cut threshold is an important part of fuzzy logic. For example, in Figure 2, the alpha-cut of 0.5 for fuzzy number *a* creates an interval of (8.5, 11.5), and the fuzzy set only contains the single-valued numbers whose membership value is higher than 0.5. The alpha-cuts are defined as sets such that $S_a^\alpha = \{x \mid \mu_a(x) > \alpha\}$. Alpha-cut of 0 of a fuzzy number is equivalent to the support of a fuzzy set; alpha-cut of 1 of a fuzzy number contains only the peak value. Alpha-cut thresholds are used as modifiers to modify fuzzy regions and fuzzy rules to improve the system performance.

In our e-Commerce DSS, we use the fuzzy number's leftmost, peak, and rightmost points to collect the fuzzy weights that customer put on product attributes. For example, the customer may feel that the brand name to him/her is at least "moderately important", at most "extremely important", and most likely "very important". The terms "moderately important", "very important", "extremely important", etc. can be associated with quantitative measures such as Likert scales. Essentially, we use the triangular fuzzy numbers to elicit and model customer's imprecise weights and preferences. This information on customer preferences will be used to form a set of qualifying or promising products to present to customers without any exact ranking.

We use fuzzy-linear model (1) to partition all the available products according to the product attributes and customer's preferences. The partition generates several sets of alternatives with different levels of desirability for the customer. For example, the first class (or set A) contains the products that match customer's preferences the best; the second class (or set B) includes the alternatives that are less desirable than the ones in set A, but are more attractive than the ones in the third class (or set C), and so on.

The typical content-based recommendation system would elicit crisp user preferences and utility values and then generates a list of recommendations ranked by the degree of attractiveness. This approach assumes that the customers know exactly their preferences on certain criteria and are able to make precise judgment on comparing alternative products, e.g. customers are capable of comparing alternatives of different brand names and assigning numbers to represent their degree of willingness to buy one alternative over the other. This may well be the case in frequent shopping. However, in the case of infrequent shopping, customers usually do not have well defined preferences and are not able to make such judgment; therefore, we use fuzzy weights to allow customers to specify their opinions on the relevance of different product attributes in "imprecise" terms.

Our system utilizes the method of ordering fuzzy numbers (Triantaphillou and Lin, 1996) to rank fuzzy utilities of all available alternative products, so that we can partition the products into several sets with different levels of desirability.

We bring in the parameter "certainty level" c to specify the level at which alpha-cut is set. The smaller the c value is, the more vagueness is tolerated in the system. When c equals to 0, i.e. its minimum value, maximum level of vagueness is tolerated; while when c equals to one, i.e. its maximum value, the method is equivalent to ordinary ranking tasks with crisp utility numbers, and the "A" set contains only one overall utility value, which refers to one product alternative or several alternatives sharing the same utility value. Therefore, the lower the certainty level c is, the more product alternatives would be considered in one partitioned set, e.g. set "A", "B", etc. We can hence define the set of utility intervals at a particular alpha-cut level to represent all the alternatives.

$$\begin{aligned} &\Omega^{\alpha} = \{S_i^{\alpha}\}, i = 1,\ldots,n \\ &S_i^{\alpha} = \{x \mid \mu_i(x) > \alpha\} \\ &\alpha = c \end{aligned} \tag{2}$$

In the above expression, $\mu_i(x)$ stands for the membership function for the utility of i^{th} product. For convenience purposes, we will also use the expression (3) – the interval containing the left and right boundaries to address S_i^{α} in the following discussions.

$$S_i^\alpha = (l_i^\alpha, r_i^\alpha) \qquad (3)$$

We can then define the reference sets or intervals which represent different grades of desirability. The first-grade or most-desired reference set (or the A reference set) is as follows:

$$S_r^{\alpha,1} = \{S_i^\alpha \mid \max_{l_i^\alpha} \max_{r_i^\alpha}(l_i^\alpha, r_i^\alpha)\} \qquad (4)$$

The A set should be the set with the largest right boundary. If there are a few sets that all have the same largest right boundary, then the one with the largest left boundary is selected to be the A set.

We can also use the expression similar to (3) to denote A reference set as follows:

$$S_r^{\alpha,1} = (l^{\alpha,1}, r^{\alpha,1}) \qquad (5)$$

The subsequent intervals or reference sets, i.e. the B set, C set, etc, can be denoted similar to (4) as follows:

$$S_r^{\alpha,j} = \{S_i^\alpha \mid \max_{l_i^\alpha} \max_{r_i^\alpha}(l_i^\alpha, r_i^\alpha), r_i^\alpha \le l^{\alpha,j-1}\}\ j = 1,\ldots,m \qquad (6)$$

In this expression, m is the grade number of the reference set, e.g. A set is when $m = 1$, B set is when $m = 2$, etc.

Therefore, the set

$$\Omega_r^\alpha = \{S_r^{\alpha,j}\} \tag{7}$$

can be divided into many non-overlapping subsets (described in (6)) that we will use for further analysis and clustering.

Finally, we can describe the super set that contains all the product alternatives and their mappings into all of its non-overlapping sequential subsets, which represent different grades of desirability, as follows:

$$\begin{aligned} &\Omega_p^\alpha = \{S^{\alpha,j}\} \\ &S^{\alpha,j} = \{S_i^\alpha \mid r_i^\alpha > l^{\alpha,j}, S_i^\alpha \notin S^{\alpha,j-1}\} \end{aligned} \tag{8}$$

The expression specifies that the subset will belong to a specific grade (j) when its interval overlaps with the corresponding reference set and not belong to a higher grade ($j-1$). In other words, if uncertainty exists when we compare a certain product with the representative product of a specific grade in terms of preferences, then the product should belong to that grade. Clustering will then be performed inside each product set of different grades, and the diverse cluster representatives of the first-grade product set will be presented to the customers through our support mechanism. Customers can also browse through products in lower-grade sets if they wish to do so.

The above equations outline our core procedures to perform the preliminary product filtering according to the fuzzy customer preferences. A simple example of applying the procedure can be demonstrated using Figure 2. If we set the alpha cut level to one, then there is no need for partitioning because all the fuzzy numbers become crisp numbers, and each grade set include only one product, i.e. the first grade set only contains product *a*, the second grade set contains product *b*, and the third grade set contains product *c*. If the alpha cut level is set to be 0.5, we will have two non-overlapping reference sets: the first grade set contains product *a* and *b*, and the second grade set contains product *c*. When alpha cut level is set to be zero, we will only have one reference set: all products belong to the first grade set, and they are considered equivalent in terms of fuzzy utility.

5.2 Generating Divergent Product Alternatives

Once we have ranked and determined the set of desirable products, we will then need to present the alternatives to the customers without cognitively overloading them. Even in the first grade product set, there could still be hundreds or thousands of product items. To address this problem, we will use the divergence-convergence principle discussed earlier. Moreover, we will employ Cluster Analysis (CA) as the primary tool to calculate the similarity or dissimilarity among the diverse product alternatives.

Cluster Analysis is a statistical tool for grouping similar objects into respective categories. Most recommender systems use cluster analysis as the basic technique to find "similarity" among customers, products, and services to generate recommendations (Schafer, Konstan, and Riedl; 2001). However, our approach is in the opposite direction in using cluster analysis; we employ cluster analysis to find the "dissimilarity" among products. This is because of the different nature of task in our case, i.e. ill-structured decision-making for infrequent purchase. We present the most dissimilar product alternatives first, and consequently according to customer's choice, we narrow down the scope of products for analysis, and then again present the most dissimilar items within the smaller group of products. Therefore, the dissimilarity among presented alternatives gets smaller and smaller from the beginning to the end of the process, until the individual product alternative is selected.

We use the Euclidian distance metric to calculate the distance for cluster analysis. More specifically, the distance between the alternative X and Y is calculated as following:

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} w_i^2 (x_i - y_i)^2}$$

In this expression, subscript i represents various product features, for example, price, brand name, producer reputation, etc. The weight w_i or the perceived importance of a given feature is a crisp number drawn from the fuzzy weights through defuzzification operation (Klir and Yuan, 1995). For the reason of simplicity, we use the peak value of the fuzzy weight triangle to calculate the distance.

We will then cluster a set of products (e.g. set A) into groups using certain clustering algorithms. In our study, we used two kinds of clustering algorithms in two prototype systems respectively: *hierarchical clustering method* and *adaptive nearest-neighbor clustering method.*

According to customer's browsing activities, both methods will offer several alternatives at every step. The alternatives are most dissimilar in the beginning of the process and become less and less diverse towards the end, until the customer chooses an individual product. We use the centroids of the clusters as the reference to determine which product alternative to present. Once we have calculated the centroids, we then find the product alternative that is closest to the centroids, and this product should have the most representative features of the corresponding cluster. When the customer decides to explore more in the neighborhood of one of the presented representative products, the system will again partition the corresponding cluster into sub-clusters, find the centroids of those sub-clusters, and present the representative product alternative of those sub-clusters. This process continues until the customer chooses a specific product. Note that the process is not linear. At any point, the customer can go back, zoom out of the neighborhood of a cluster, and zoom into other clusters.

Figure 3 gives a simple example of this process with *hierarchical clustering method.* Let's assume that we present two product alternatives to the customer at each step (note that the number of alternatives to present is flexible and can be set up according to different needs). To begin with, two representative products from the cluster (a, c) and the cluster (e, b, d) will be given to the customer, and the representatives in this case would be a (or c) and b. The customer may then choose to explore the neighborhoods of these two clusters. If the customer choose to explore the vicinity of the cluster (e, b, d), two sub-clusters (e) and (b, d) will be examined, and the representatives of these two sub-clusters e and b (or d) will be presented to the customer. The customer can move forward to examine the clusters of (b) and (d), or s/he can go backwards and explore other clusters.

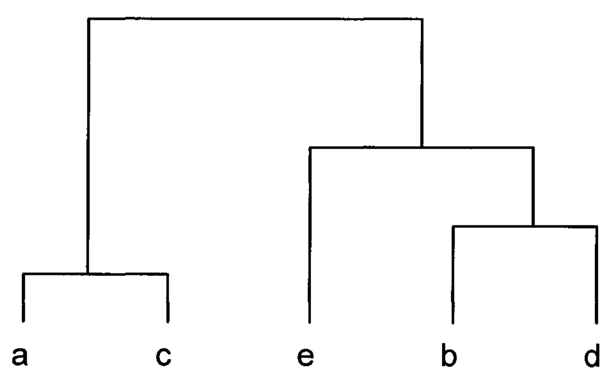

Figure 3 Example dendrodram for five products (hierarchical clustering method)

Figure 4, 5, and 6 explain how the *adaptive nearest-neighbor clustering method* works. Firstly, we define product categories/clusters and their initial anchors. Here let's assume that we have determined three product categories and their anchors according to price and other utilities (shown as squares in Figure 4: Budget anchor, Value anchor, and Luxury anchor). After that, according to these predetermined anchors, we cluster product items (shown as stars in Figure 4) according to their nearest-neighbor anchor. For example, in Figure 4, to determine which cluster "product item 1" belongs to, we first calculate the distances between product item 1 and Budget anchor *d(b)*, Value anchor *d(v)*, and Luxury anchor *d(l)*. In this case, the shortest distance is *d(v)*, and therefore product item 1 belongs to the Value cluster.

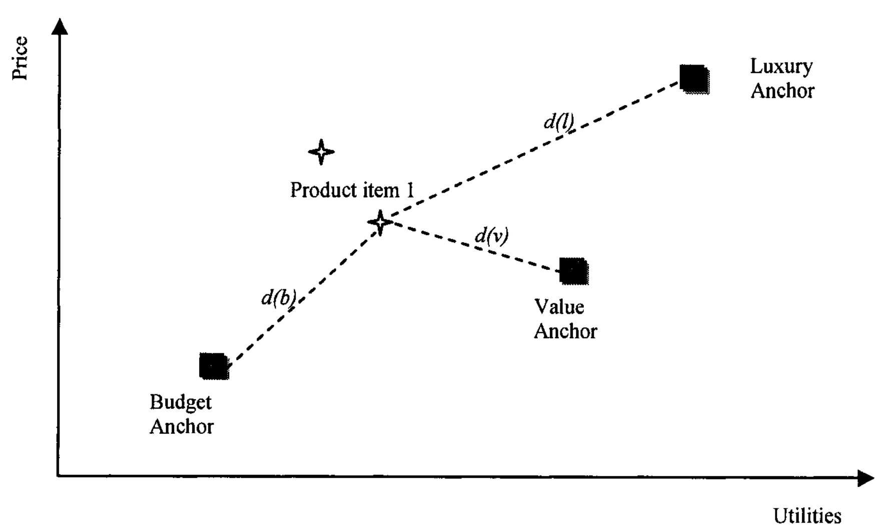

Figure 4 Example of nearest-neighbor clustering method

Thereafter, the anchors dynamically adapt their positions according to the customer's interactions with the system. Figure 5 and 6 depict such movements of the anchors. Let's assume that the customer has chosen to explore the Value cluster and has sent such information to the system. All the anchors will then move towards the pre-set Value anchor by a factor of *alpha* (alpha is used in the case of anchors of different clusters, e.g. Budget anchor to Value anchor and Luxury anchor to Value anchor; see Figure 5) and a factor of *beta* (beta is used in the case of anchors of the same cluster, e.g. Budget anchor to pre-set Budget anchor; see Figure 6). In Figure 5, we can see that, after the anchors have moved towards the pre-set Value anchor, the product item 1 now belongs to the Budget cluster because it has the shortest distance to the new Budget anchor than to the other two effective anchors. By doing this, the system adjusts and focuses itself to the customer's interests. Also, we can modify the sensitivity of such adaptation by changing these factors alpha and beta. In this study, both alpha and beta are set to 0.1.

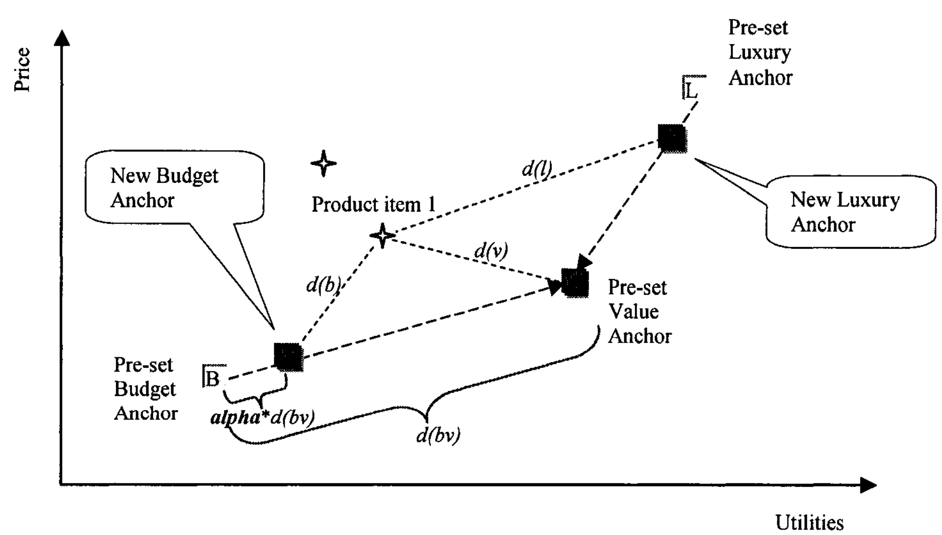

Figure 5 The adaptive factor alpha in nearest-neighbor clustering method

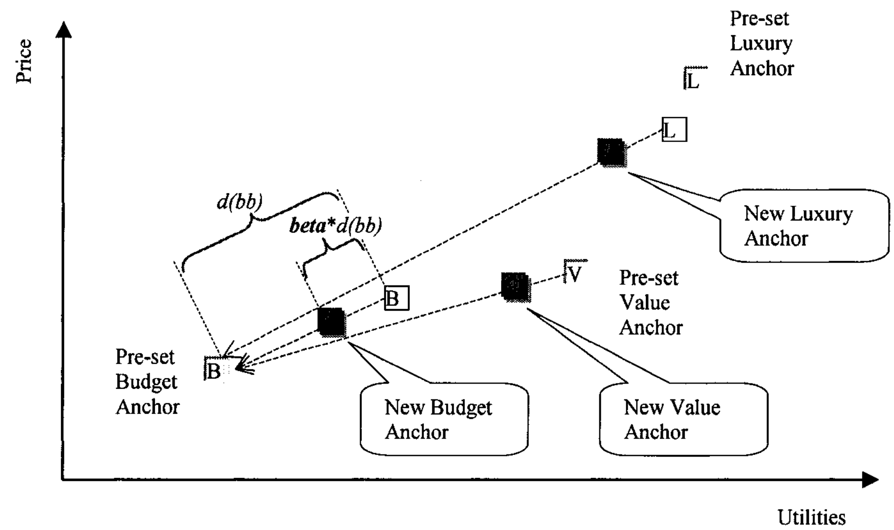

Figure 6 The adaptive factor beta in nearest-neighbor clustering method

6 Decision Support System for E-commerce Buyer Support

6.1 Architecture for Buyer DSS

The architecture of our decision support system for e-commerce buyer support is on Figure 7.

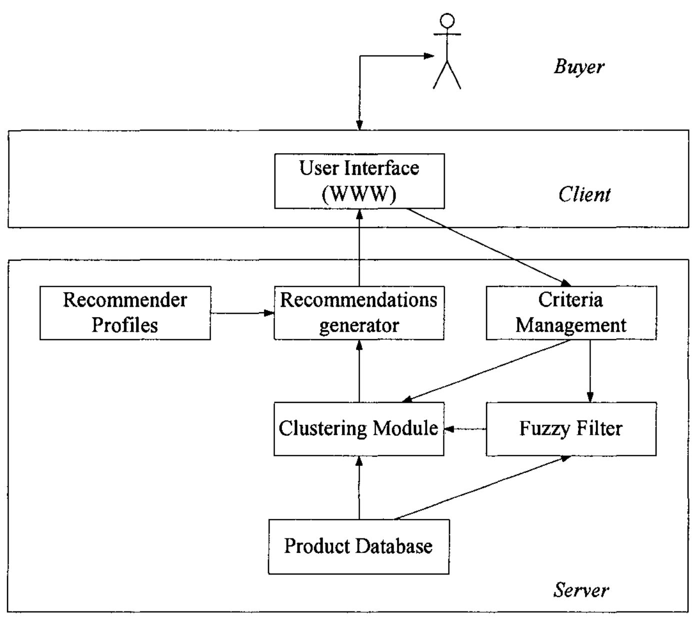

Figure 7 Architecture of buyer DSS

The *criteria management module* manages and records user preferences on preset criteria. The users specify their perceived relative importance on certain product features in fuzzy terms; they can also rule out certain criteria which they consider being insignificant. In our approach, the purpose of gathering this information is not to recommend the optimal choice to the customer. The traditional optimal recommendation approach would not be efficient with ill-defined preferences; rather, it would limit the user's opportunity to explore more interesting alternative solutions. We will expose the customers to all possible solutions in such a way that the customers can easily find their own optimal choice. The preference information we gathered in this module is used to calculate the distance metric between the products, so that we can offer the most diverse alternative solutions to the customer. For example, if the price were of prime importance to the customer, the presented alternatives would differ most in the price dimension.

Taking the user preference information from criteria management module and the product attributes from product database, the *fuzzy filter module* calculate the fuzzy "grades" for all product alternatives. Based on these grades (i.e. fuzzy triangles), the alpha-cut (the certainty level) is used to determine the number of alternatives in the "A" set and other grade sets. The certainty level is initially set to be 0.5 and can be modified to change the number of alternatives in the "A" set and the alike. This single parameter can be used to control the minimum quality of the A set. It implies the level of certainty that customer has in various aspects of the product. The more certain they are (i.e. the less fuzzy their preference expressions are), the less alternatives they will need to examine. In other words, when the customer is not certain about their preferences, their investigation would cover wider range of products in order to explore more opportunities that are available and make the best and informed choices. This parameter can also be attuned to the individual decision-making style of the customers. The fuzzy filter module generates the partitions with different grades of desirability, and passes this information to the clustering module for generating clusters inside these partitions.

The *clustering module* executes cluster analysis to discover the dissimilar product classes in order to present the most different suggestions. The "A" set (or other grade sets with lower desirability) is divided into dissimilar clusters using hierarchical clustering method or nearest-neighbor method. The representative product of each cluster is presented to the customer. The maximum number of alternatives presented to the customer (i.e. the maximum number of clusters in the A set and the alike) can be determined in advance or automatically. Moreover, to avoid cognitive overload to the customer, this number should be reasonably small. In our system, we set this number to be three.

The *recommender profiles module* represents the rationale behind the recommendations generated by the system. It relates the key "values" of the customers with the features of the recommended products. As discussed earlier, this is inline with the means-end theory on web browsing activities which suggests that customer's choice on certain product attributes is essentially a means to attain certain personal values (Subramony, 2002; Miles and Howes, 2000). We incorporate different values in the system in order to help with customer's decision-making process, such as "budget", "value" and "luxury" consuming categories. These three profiles are partially based upon price frames. This is in accordance with Smith and Wortzel (1997)'s finding that novice customers are affected by the price frames of reference where price is used as a "heuristic cue" to indicate product quality.

We define these recommender profiles with relative product features as opposed to absolute ones. In the system interface, the recommended alternatives are labeled with the profiles together with a confidence level (e.g. "luxury" with a confidence level of 90%). The confidence level is the percentage of matching between the product features and the profile.

6.2 Prototypes for Notebook Selection

To test the effectiveness of the method, we developed two prototype systems for notebook selection, with ASP.NET and VB.NET. The database is running on SQL server 2000; the relationship diagram of the database design is shown in Appendix A. The database is populated with real notebook data from www.dealtime.com, and it contains 247 notebook computer records with very diverse product features (prices range from $479 to $8220 Canadian dollars), which will fully allow us to present diversified alternatives and observe the effectiveness of the system in creating divergent suggestions. We've chosen "price", "brand name", "producer", "supplier", "CPU", "memory", "hard drive", and "screen size" as the key product attributes. All the attribute utilities are converted to relative crisp numbers within the range of [0, 1]. The attribute values for price, CPU frequency, memory, hard drive, and screen size are calculated from its original numeric scales, while the ones for CPU type, brand name, producer, and supplier are from expert ratings. As we discussed earlier, to help novice customers better understand and evaluate the product attributes, we need to help them form personally relevant means-end inferences. To accomplish that, a glossary module is included in the Product details page (Appendix B: Screenshot of the product page in the experiment) where the product attributes are explained with their consequences and benefits.

Figure 8 is the screen shot where customers are asked to give their perceived importance of the key product attributes. The interface allows the customers to express their vague preferences. For example, the price can be at least somewhat importance (Likert-scale value 4), most likely fairly important (Likert-scale value 5), and at most very important (Likert-scale value 7). This defines a fuzzy weight triangle with the peak value of 5 and the support (4, 7).

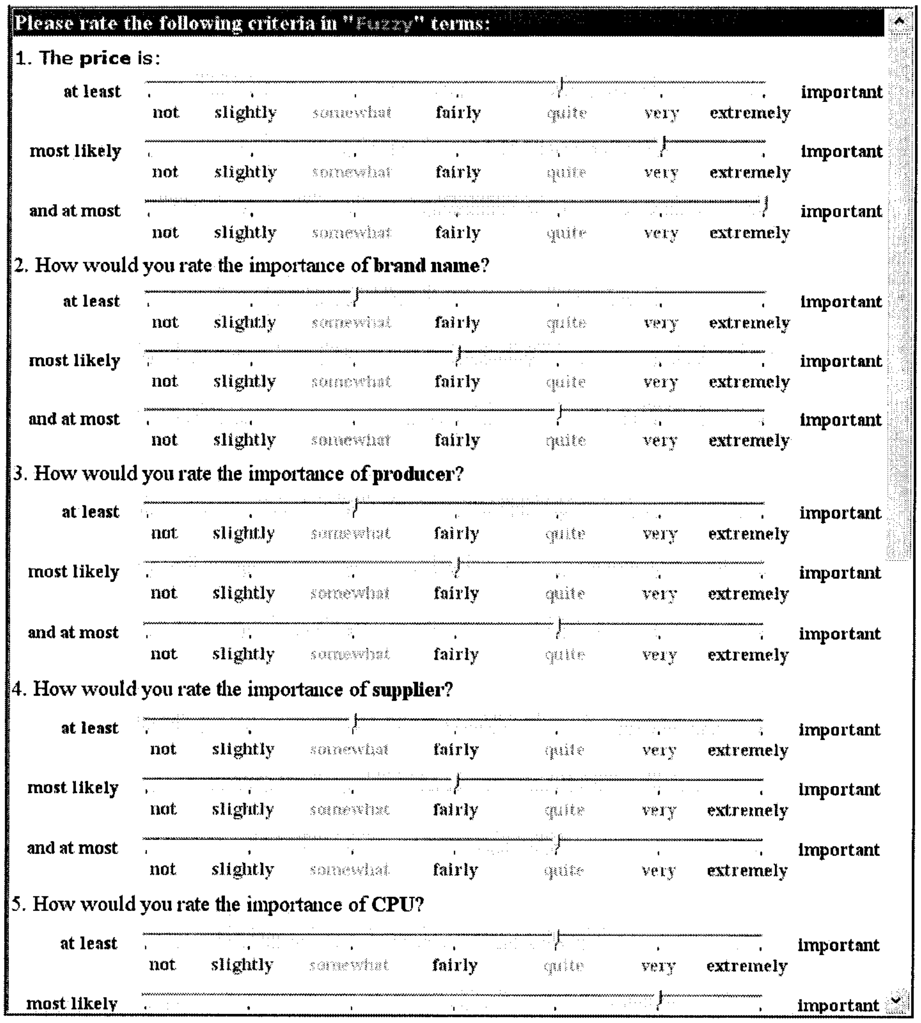

Figure 8 Screenshot of the interface for defining fuzzy weights.

The following demonstrates a scenario of selecting notebooks for class "A" set. Table 2 is a sample portion of product database with twelve notebook records in it. Table 3 contains the same information as Table 2 except that the original scales are converted into relative utilities within the range of zero to one. Note that the lower the price, the higher the utility.

Table 2 Portion of product database

ID	CPU Ranking	CPU Frequency	Memory	Hard Drive	Screen Size	Producer Ranking	BrandSeries Ranking	Supplier Ranking	Price
1	35	300	64	4.3	14.10	85	50.10	50	$538.50
2	65	1800	256	30	15.00	95	20.50	50	$1,744.49
3	65	1800	256	30	15.00	95	20.40	50	$1,828.49
4	65	1800	256	30	15.00	95	20.40	50	$1,944.53
5	45	1200	256	30	12.10	95	390.40	50	$2,136.00
6	45	1200	256	30	12.10	95	390.40	50	$2,309.93
7	75	1800	256	40	14.10	90	220.10	50	$2,518.43
8	75	2400	512	30	15.00	95	390.30	50	$2,698.50
9	75	1700	256	40	12.10	95	30.50	50	$2,849.93
10	75	2000	256	40	14.10	90	220.10	50	$2,994.21
11	75	2000	512	40	15.00	80	330.10	80	$3,399.99
12	70	2000	256	60	15.00	90	230.10	50	$4,522.50

Table 3 Portion of product database expressed as utilities

ID	CPU Ranking	CPU Frequency	Memory	Hard Drive	Screen Size	Producer Ranking	BrandSeries Ranking	Supplier Ranking	Price
1	0	0	0	0	0.6897	0.333333	0.08027027	0	1
2	0.75	0.714286	0.4286	0.461	1	1	0.00027027	0	0.6972929
3	0.75	0.714286	0.4286	0.461	1	1	0	0	0.6762086
4	0.75	0.714286	0.4286	0.461	1	1	0	0	0.6470821
5	0.25	0.428571	0.4286	0.461	0	1	1	0	0.5990211
6	0.25	0.428571	0.4286	0.461	0	1	1	0	0.5553652
7	1	0.714286	0.4286	0.641	0.6897	0.666667	0.53972976	0	0.5030309
8	1	1	1	0.461	1	1	0.99972971	0	0.4578313
9	1	0.666667	0.4286	0.641	0	1	0.0272973	0	0.419823
10	1	0.809524	0.4286	0.641	0.6897	0.666667	0.53972976	0	0.3836069
11	1	0.809524	1	0.641	1	0	0.83702706	1	0.2817545
12	0.875	0.809524	0.4286	1	1	0.666667	0.56675678	0	0

Table 4 gives a simplistic sample fuzzy weights from customer. This customer assumes that all the attributes are equally important to him/her, and the weights all have the peak at the medium with the widest support.

Table 4 Fuzzy weights

Weight	CPU Ranking	CPU Frequency	Memory	Hard Drive	Screen Size	Producer Ranking	BrandSeries Ranking	Supplier Ranking	Price
Min	1	1	1	1	1	1	1	1	1
Peak	4	4	4	4	4	4	4	4	4
Max	7	7	7	7	7	7	7	7	7

Figure 9 depicts the fuzzy utilities of these twelve alternatives. The corresponding values of these fuzzy triangles are in Table 5, and the calculation is based on the equation (1). As we can see from Figure 9, when the certainty level (alpha-cut level) is set to be one, twelve different grade sets are generated because each and every product will form its own grade set. When the certainty level is set to be zero, all twelve alternatives belong to the same grade set, and i.e. they are utility-equivalent. When the certainty level is set to be 0.5, two reference sets are created; the class "A" set contains eleven products with the representative product No. 8, and the class "B" set (second grade) only contains and therefore represented by the product No. 1. The dashed lines in Figure 6 indicate the reference sets.

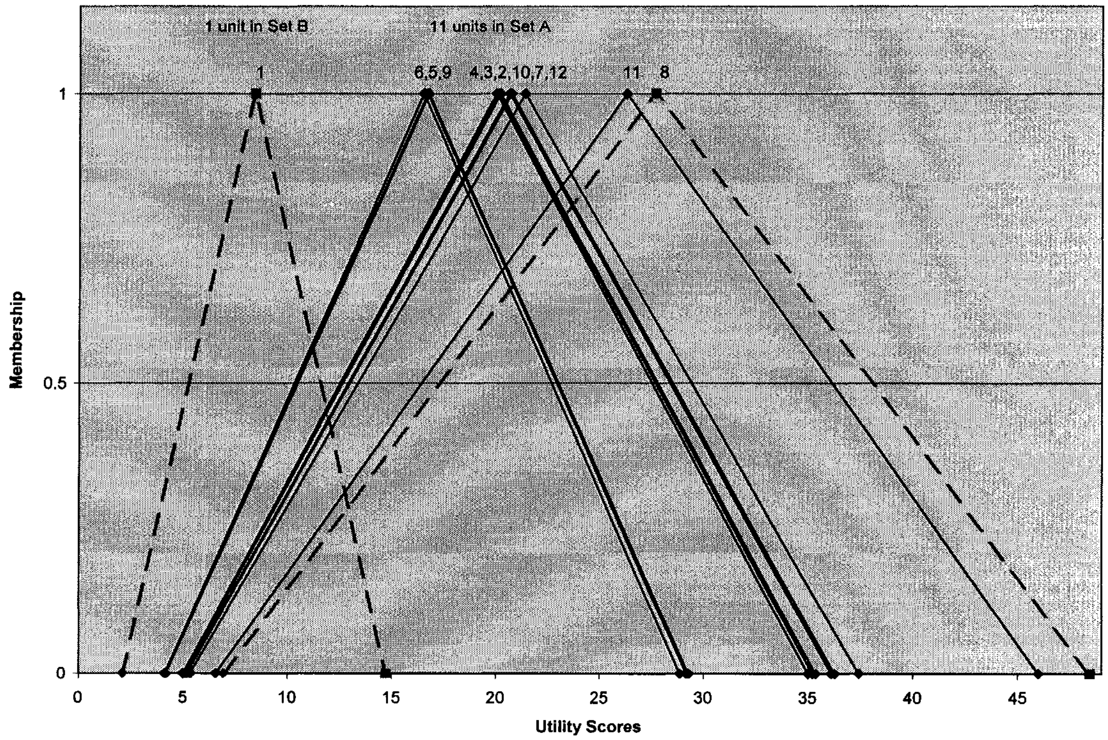

Figure 9 Fuzzy utilities of alternatives

Table 5 Fuzzy utilities of alternatives

Alternative	Fuzzy Utilities		
	l	p	R
1	2.103258865	8.41303546	14.72281205
2	5.051820695	20.20728278	35.36274486
3	5.030466086	20.12186435	35.2132626
4	5.00133958	20.00535832	35.00937706
5	4.167564301	16.6702572	29.1729501
6	4.123908427	16.49563371	28.86735899
7	5.182873274	20.7314931	36.28011292
8	6.918961398	27.67584559	48.43272978
9	4.183292009	16.73316804	29.28304406
10	5.158687424	20.6347497	36.11081197
11	6.569238958	26.27695583	45.9846727
12	5.346518688	21.38607475	37.42563081

Giving "less fuzzy" fuzzy weights (or setting narrower fuzzy weight triangles) means that the customer is more certain about his/her preferences on the product. In that case, the system is able to identify and screen out more less-desired alternatives from the class "A" set. Table 6 demonstrates a sample set of fuzzy weights in such a scenario. Calculated with these fuzzy weights and the original notebook attributes in Table 2, the new fuzzy utilities are illustrated in Table 7 and Figure 10.

Table 6 Fuzzy weights: second scenario

Weight	CPU Ranking	CPU Frequency	Memory	Hard Drive	Screen Size	Producer Ranking	BrandSeries Ranking	Supplier Ranking	Price
Min	5	5	3	3	3	3	3	3	5
Peak	6	6	4	4	4	4	4	4	6
Max	7	7	5	5	5	5	5	5	7

Table 7 Fuzzy utilities of alternatives: second scenario

ID	Goodness		
	I	P	R
1	8.309776595	10.41303546	12.51629432
2	19.47861936	24.53044005	29.58226075
3	19.37238686	24.40285294	29.43331903
4	19.22675433	24.22809391	29.22943349
5	15.05787793	19.22544223	23.39300653
6	14.83959856	18.96350699	23.08741541
7	19.983253	25.16612627	30.34899955
8	25.67254684	32.59150824	39.51046964
9	16.72285544	20.90614745	25.08943946
10	19.86232375	25.02101117	30.17969859
11	23.89027353	30.45951249	37.02875144
12	19.40860368	24.75512237	30.10164106

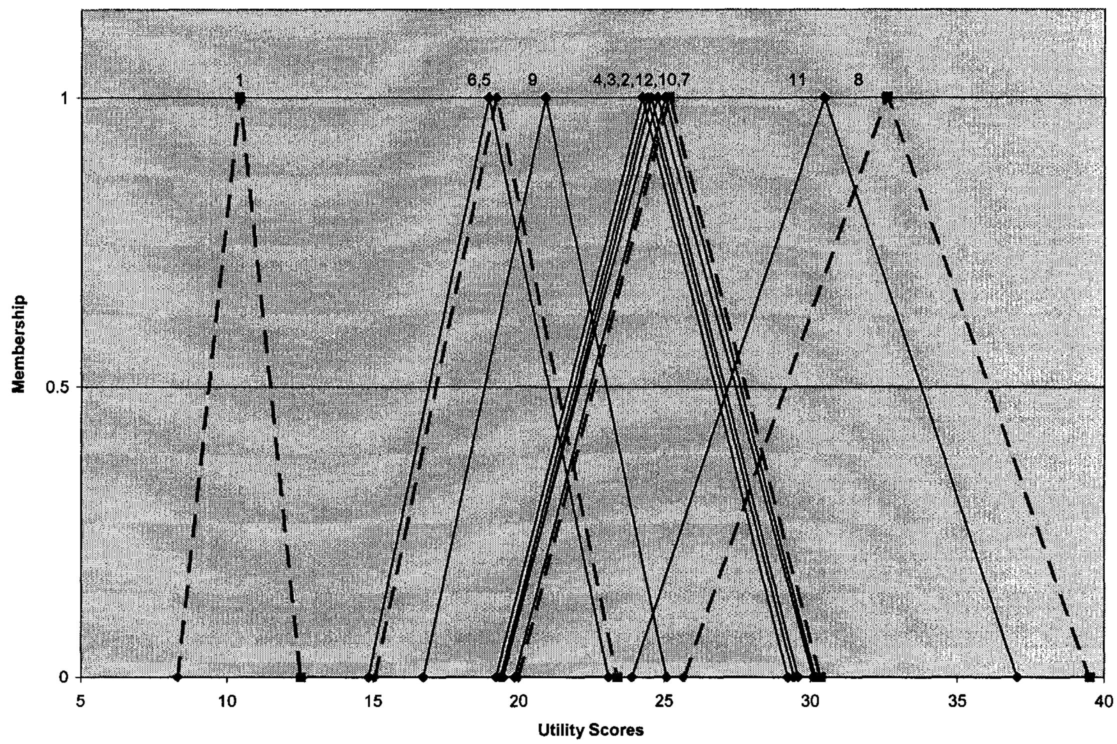

Figure 10 Fuzzy utilities of alternatives: second scenario

As we can see from Figure 10, when the certainty level is set to be zero, there will be three reference intervals and therefore three grade sets represented by alternative No. 8, No.9, and No. 1. When the certainty level is set to be 0.5, four reference intervals are formed. The reference sets are shown with dashed lines in Figure 10, and they are represented by alternatives No. 8, No. 7, No. 5, and No. 1.

Table 8 shows that the number of alternatives in each grade set changes with the certainty level. As we can see from this summary, when the certainty level goes up, the alternatives are more spread out to higher-grade classes (note that the higher the grade, the less attractive the set is), which also means that the system becomes more restrictive in classifying products into different grade sets.

Table 8 Summary of fuzzy filtering with twelve alternatives

Certainty level	Set A	Set B	Set C	Set D
0	8	3	1	0
0.5	2	7	2	1
1	1	1	1	1 …

Once the system finishes classifying the alternatives into different grade sets, we use Cluster Analysis methods to cluster the alternatives in the class A set, and in our study, we implemented two methods in two prototype systems respectively. In the system interface, we have chosen to present maximum three alternatives at a time. From the divergent perspective, these three alternatives would differ according to the combination of customer preferences and product attributes. For example, if the customer stresses on price, the alternatives would differ greatly in price.

As mentioned earlier, we also label these three (or less) alternatives with “budget”, “value”, and “luxury” profiles together with a confidence level. The “budget” profile looks for minimum prices and at the same time compromises the quality; the “luxury” profile, on the other hand, seeks maximum quality while tolerates high prices; the “value” profile, a midway solution, asks for good quality with reasonable prices. Although we think that the profiles would be more appropriately defined with fuzzy sets, in the prototype systems we only used a simple crisp profile structure for calculation. A simple formula which adds up product utilities (as shown in Table 3) is used to obtain an overall score for comparing against the profiles. We define the product item with the best attributes and most likely the highest price as the "luxury" profile, the item that has the lowest score as the "budget" profile, and the item that scores in the middle of those two extremes as the "value" profile. The Figure 11 depicts these three profiles mapping on the addictive scores.

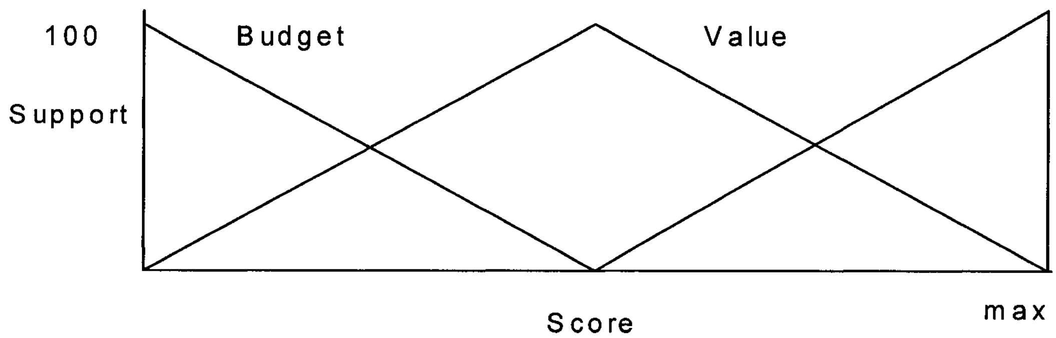

Figure 11 Recommender profiles.

The two prototype systems, with hierarchical clustering method and nearest neighbor method, although very different in generating clusters within a certain grade set, are quite similar in terms of divergent/convergent alternative presentations. We will explain the differences and show in detail how these two methods work in prototypes in the following sections.

6.2.1 Prototype System Using Hierarchical Clustering Method

Figure 12 is a screenshot of the prototype system suggesting three diverse alternatives, which represent three diverse clusters of notebooks. These three items fall under the profile budget, value, and luxury sequentially; the confidence level of matching between the product and the profile is also presented. The link button "Search Similar" will let users zoom into the corresponding cluster; upon clicking on the link button, three sub-clusters will be generated with three new representative alternatives showing on the screen. Note that the three diverse alternative suggestions come from "Best-match notebooks" class, i.e. grade A set. If the customer has not find the product of choice after browsing the grade A set, or if s/he wants to investigate more notebooks, s/he can continue the search in the "2nd-match notebooks", i.e. grade B set (see Figure 13).

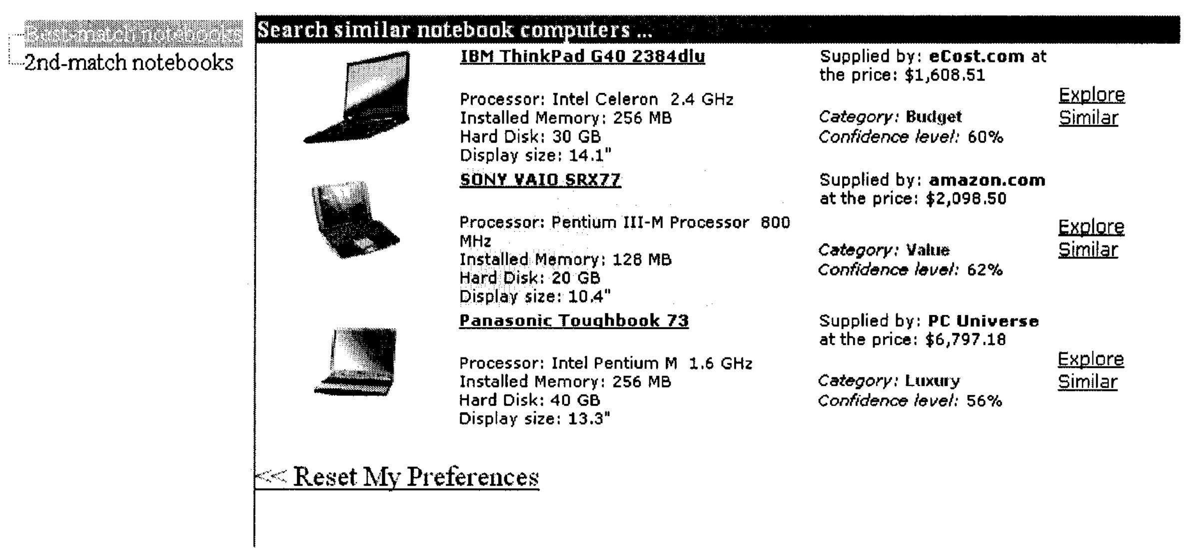

Figure 12 Screenshot of the prototype system with hierarchical clustering method.

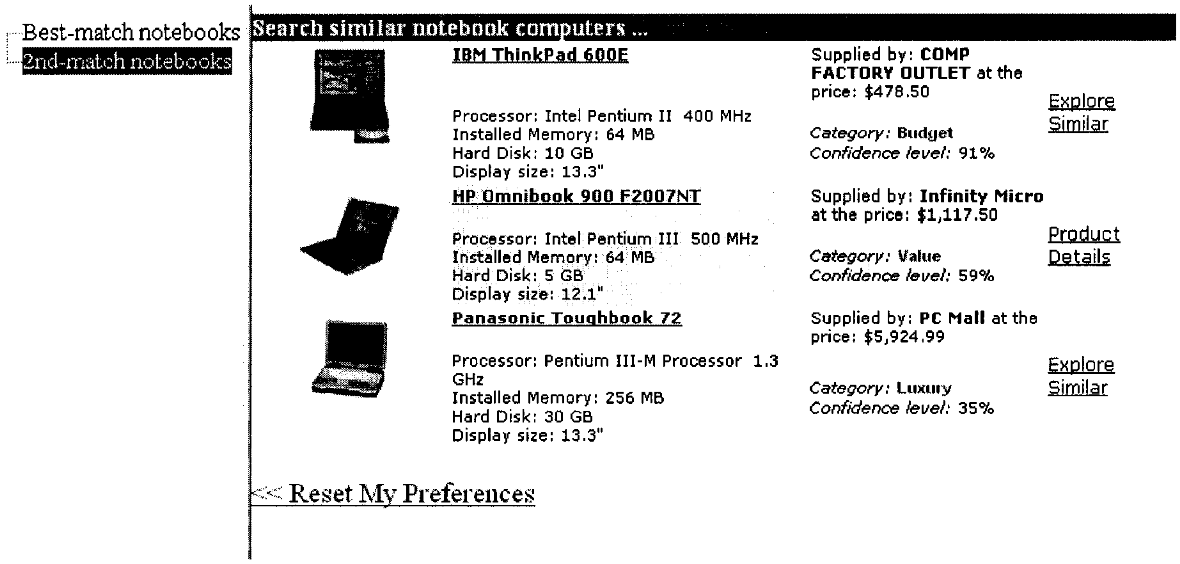

Figure 13 Grade B set diverse suggestions in the prototype with hierarchical clustering method

Marketing researchers have found that customers process price information differently and separately than other product attributes (Ahtola, 1984; Park and Lessig, 1981). This is likely caused by the give-and-get mentality in customers' purchase decision process, where customers give/sacrifice the money (or time, effect, etc.) to get/receive certain results/benefits from other product attributes (Zeithaml, 1988). For this reason, in the interface design of our system, we highlight the price by showing it as the last attribute with extra amount of surrounding space, together with price-framed profiles (e.g. luxury). Also, in calculating the overall utility of a product item, we negate the price utility by setting highest price utility for the lowest price value (and vice versa), and thus to reflect the give-and-get relationship between price and other attributes.

From Figure 12, if we continue clicking on "Explore Similar" under the Luxury category, i.e. we zoom into the luxury notebook neighborhood, we will get less diverse suggestions; in other words, the presented alternatives will be more and more similar to each other. This is shown consecutively in Figure 14 and Figure 15. We can see that Figure 15 offers three alternatives of the same model only with different prices from different suppliers.

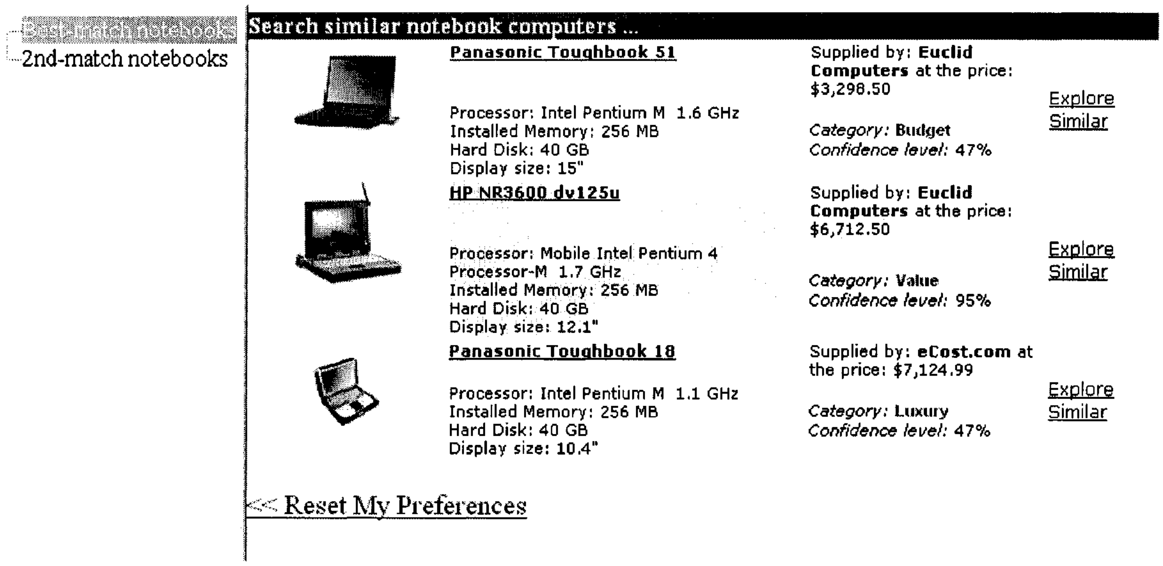

Figure 14 less diverse suggestions comparing to Figure 12 when zoomed into Luxury category.

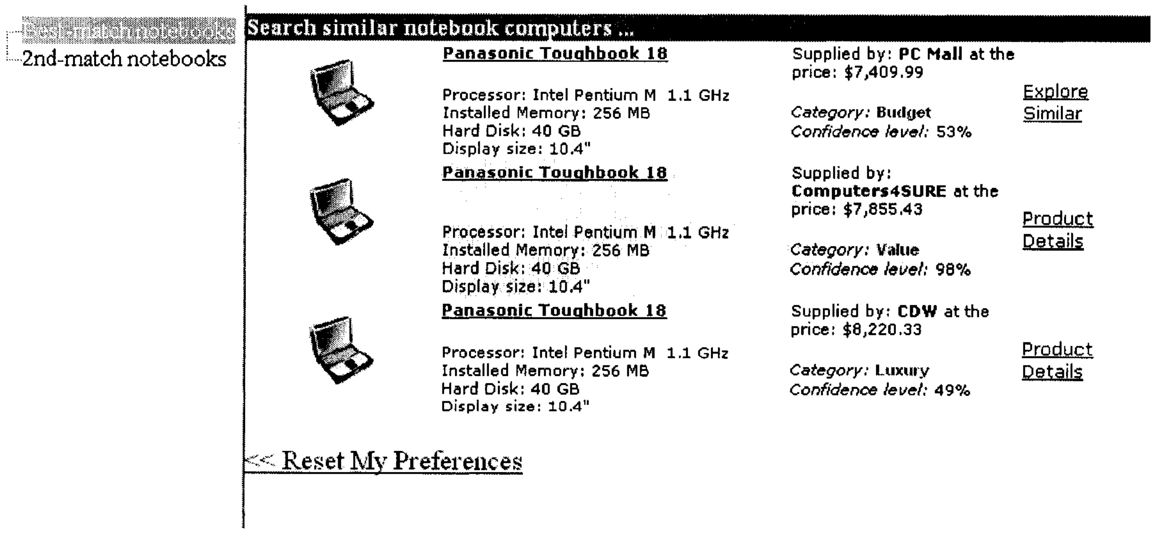

Figure 15 Even less diverse suggestions comparing to Figure 14 when zoomed again into Luxury category.

With the hierarchical clustering method, once the system gets user preferences and product attributes, the cluster centroids are all calculated and become fixed during users' browsing through various clusters. If the users reset or modify their preferences, the cluster centroids will be re-calculated and become fixed again. The centroids will not change upon users' selection on any clusters. However, with the adaptive nearest neighbor method, the cluster centroids move with customer's interests in cluster categories. This difference was explained in section 5.2 and will be further demonstrated in the following section.

6.2.2 Prototype System Using Adaptive Nearest Neighbor Method

Figure 16 is a screenshot of the prototype system with the nearest neighbor method. It gives three diverse alternative suggestions from the pre-set cluster anchors (i.e. Budget, Value, and Luxury anchors)

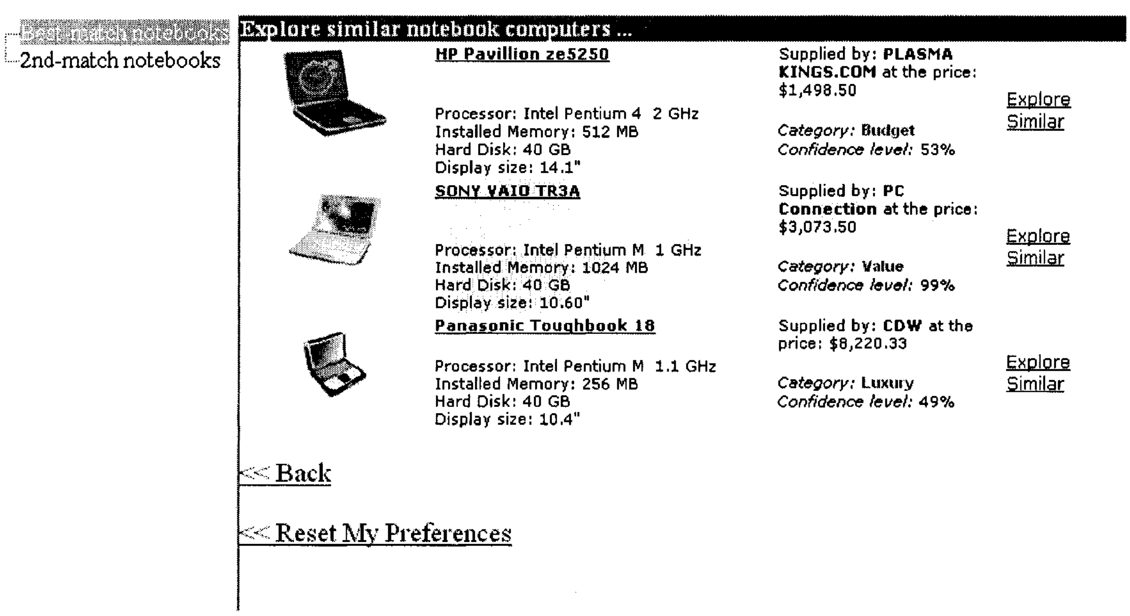

Figure 16 Screenshot of the prototype with nearest neighbor clustering method.

Now from Figure 16, if we keep exploring on the Value category, we can get pages like Figure 17 and Figure 18. The presented alternatives for Budget and Luxury clusters get closer to the alternative for Value cluster.

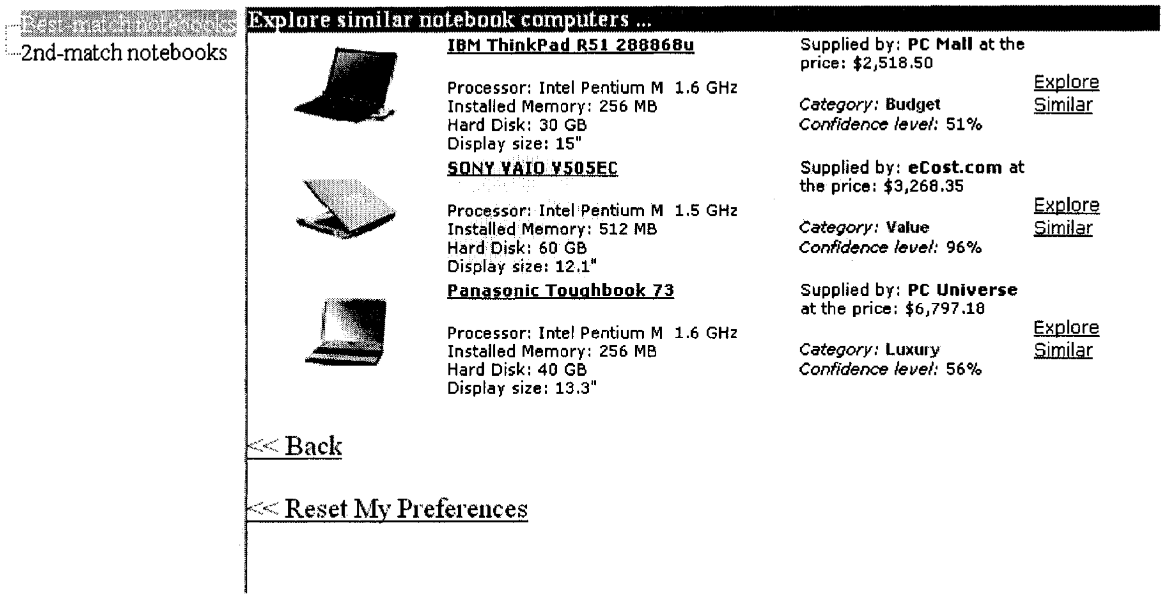

Figure 17 Adapted cluster anchors move towards pre-set Value anchor (comparing to Figure 16).

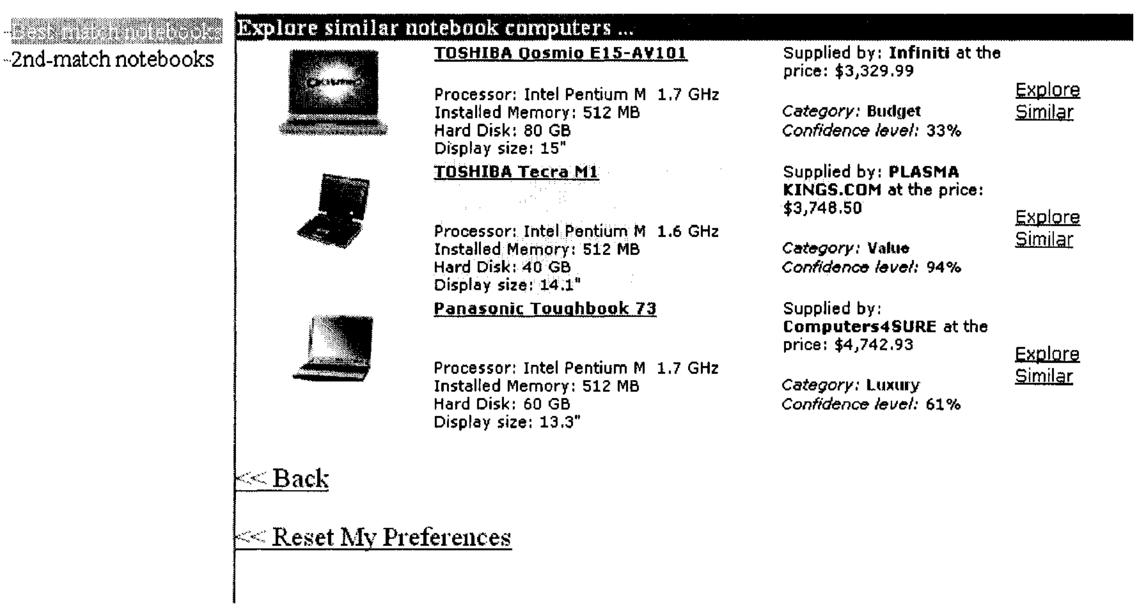

Figure 18 Adapted cluster anchors move towards pre-set Value anchor (comparing to Figure 17).

Moreover, the adaptation (or the adjustment of the anchors) carries on when we zoom out and go back to the most diverse offers in the current grade set, as shown in Figure 19. Comparing Figure 16 and Figure 19, we will find that the Budget and Luxury representative items come closer to the Value representative. This is because the Budget and Luxury cluster anchors moved towards the Value anchor, and so are the movements of the clusters.

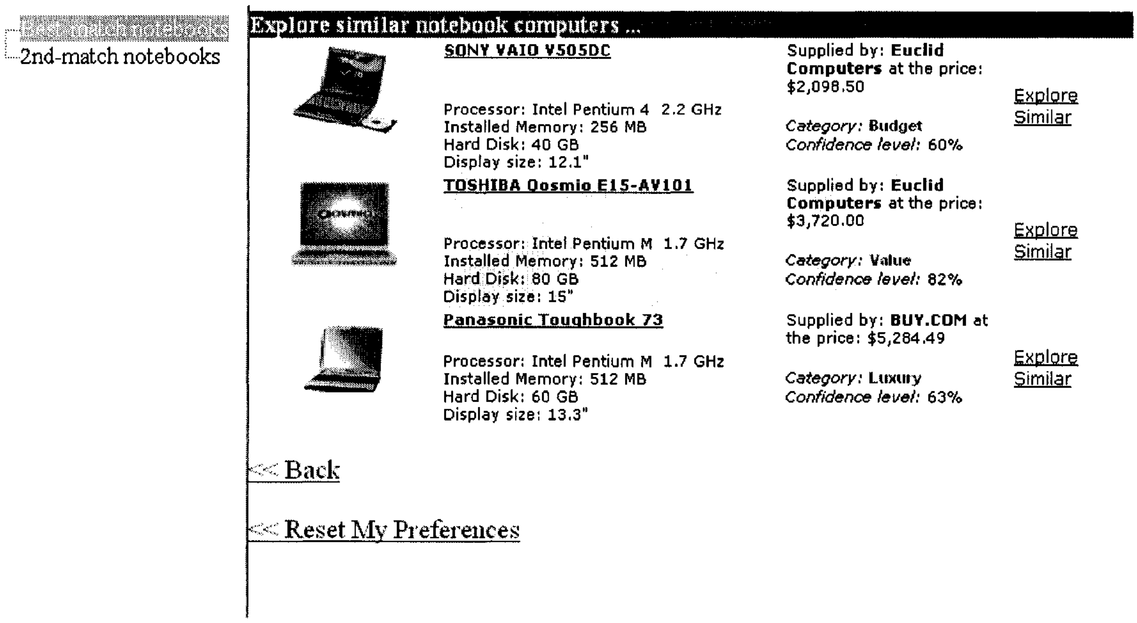

Figure 19 Most diverse alternatives with adapted cluster anchors (comparing to Figure 16).

6.3 Hypotheses and Measures

Our approach of buyer support facilitates e-commerce customer's decision making processes by first offering divergent alternative product information and then gradually narrowing down to convergent choices. In doing so, it assists all the three e-commerce goal-driven activities identified by Miles et al. (2000), i.e. "search for product", "management of search criteria", and "comparison of products". It especially tunes in the needs of infrequent novice customers by allowing them to express vague preferences and enhancing their understanding about the products with better means-end chain connections. Therefore, we believe that our approach is more effective in supporting e-customers of infrequent purchases than traditional approaches, for example, catalog system.

The hypotheses of this research take *type of decision support systems* (Our DSS systems vs. traditional catalog system) as independent variable, customer's *product knowledge* as moderating variable, and the *effectiveness of the decision support system* as the dependent variable. The reason why "product knowledge" is treated as moderating variable instead of independent variable is that customer knowledge per se does not make the effectiveness of the system; rather, it affects the level of relationship between type of systems and effectiveness of the system.

Therefore, in the following H1a, H1b, H2a, and H2b, we hypothesize that our approaches of DSS for supporting e-commerce buyers are more effective than traditional catalog system and that product knowledge plays a moderating role in determining the effectiveness of the system. In addition, our approach is aiming to assist the infrequent novice shoppers, and therefore we expect that the novice customers would be more effectively supported by the system than the expert customers would do.

H1a: The fuzzy divergence/convergence DSS with hierarchical clustering method for infrequent purchased product is more effective than traditional catalog system.

H1b: The fuzzy divergence/convergence DSS with nearest-neighbor clustering method for infrequent purchased product is more effective than traditional catalog system.

H2a: The fuzzy divergence/convergence DSS with hierarchical clustering method for infrequent purchased product is more effective in supporting lower-knowledge customers than higher-knowledge customers.

H2b: The fuzzy divergence/convergence DSS with nearest-neighbor clustering method for infrequent purchased product is more effective in supporting lower-knowledge customers than higher-knowledge customers.

We use the traditional catalog system as the base system for comparison is because both DSSs and catalog system primarily offer browse capability. We did not include the directed search capability in our study because it may bring in confounded errors.

Self-report measures are used to assess system effectiveness as well as product knowledge. To measure the effectiveness of the systems, we use *user satisfaction with the system process*, *user satisfaction with the system outcome*, the *intention to return*, and *perceived usefulness* as proximal measures or subscales. Whether or not the designed system is effective depends on how people perceive the assistance that they have received from the system. To obtain this information, we need to use self-report measures because they are the most direct way to get people's thought processes. Moreover, the use of multiple measurement modalities should increase the content validity of the measure because their different emphases and complementary effects will improve the overall measurement quality.

User satisfaction with the system process (Vahidov, 2000) is a well-developed measure that has been validated to assess the effectiveness of the system. Cronbach's alpha for the instrument was reported to be 0.9476, indicating a high level of the inter-item reliability. Construct validity was also tested using factor analysis. It has four items (seven-point scale from "strongly disagree" to "strongly agree"):

- The system helped me find the notebooks that I was interested in.
- The system provided an adequate support in performing information searching.
- I am satisfied with the help provided by the system.
- The way the notebook information is presented is useful.

The measure *user satisfaction with the system outcome* is adopted from Paul, Seetharaman, and Ramamurthy (2004), an alpha of 0.773 was originally found for the measure, and we included three items (seven-point scale from "strongly disagree" to "strongly agree"):

- The search results meet my expectations.
- I am satisfied with the search outcome.
- The system output was comprehensive.

The measure *intention to return* is adopted from Palmer (2002). Palmer used it to measure website usability, design, and performance. The ISO definition of usability is "the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use" (Karat 1997, p. 34). Therefore, usability covers the effectiveness aspect of the product, and hence *intention to return* can be used to reflect the effectiveness of the system embedded within the webpage. Three items are adapted (seven-point scale from "strongly disagree" to "strongly agree"):

- If you had a future need for information/service presented in this website, how likely is it that you would consider returning/using the website with this kind of decision support system?
- I intend to browse the website with this type of decision support system again in the near future if I need information/service presented in this website.
- I intend to browse the website with this type of decision support system frequently in the future.

The measure *perceived usefulness* is adopted from Davis (1989), and it is a well-known measure to assess systems. We employed the following four items (seven-point scale from "strongly disagree" to "strongly agree"):

- The system would enable me to accomplish notebook-searching/shopping more quickly.
- The system would enhance my effectiveness on searching/shopping for notebooks.
- The system would make it easier for me to search/shop for notebooks.
- I would find the system useful in my searching/shopping for notebooks.

All measures had high reliability rate in previous studies.

A single measure of *product knowledge* is created by including four indicators of notebook knowledge: (a) computer expertise, (b) notebook knowledge (c) actual notebook use, and (d) notebook experience. The computer expertise is measured with self-reported computer skills on a 4-point scale (labels = "poor", "fair", "good", and "excellent"). Similarly, notebook knowledge is measured by a 4-point scale on "how is your knowledge about notebook computer hardware?". The actual notebook use is measured by a 5-point scale on "how often do you use notebook computers?" (bipolar labels = "never"/"very often"). Finally, the notebook experience is measured by the number of years of notebook computer usage.

Experiments and Results

To test the effectiveness of our system, we have conducted a pilot test and a full-scale experiment. The pilot experiment tested the prototype with the hierarchical clustering method, while the full-scale experiment tested prototypes of both clustering methods. More than one hundred subjects including Concordia University students and WebHelp Inc. employees participated the web-based experiment. As an incentive, a five-dollar reward was given to each participant from Concordia University.

The experiment started with a brief introduction by the experiment instructor and then the explanatory information on the first webpage of the experiment (Appendix B: Screenshot of the description page in the experiment). The participants were asked to assume the role of an online notebook computer shopper or information seeker, to browse one type of notebook frontstore sites, and find the notebook computer that they may wish to buy. They were also given the procedure information about the questions on general demographic information and the questionnaire concerning their satisfaction with the system that the site offers. Participants then went to the next page of "consent form to participate in the research", where detailed procedural information was given and participants' agreement to participate was elicited (Appendix B: Screenshot of the consent form in the experiment). Thereafter, the demographic information is collected (Appendix B: Screenshot of the demographic form in the experiment), and the participants were randomly assigned to one of the three systems in the experiment: Catalog-based system, DSS with hierarchical clustering method, and DSS with nearest-neighbor clustering method. The participants then browsed through the notebooks and indicated their intention to purchase by clicking on the "Buy Now" button on the product page (Appendix B: Screenshot of the product page in the experiment). A Questionnaire was then presented to the participants to measure their satisfaction with the system process, satisfaction with the system outcome, the intention to return, and the perceived usefulness of the system (Appendix B: Screenshot of the questionnaire page in the experiment). Appendix C presents the complete list of the questions. After completing the questionnaire, the participants were debriefed and dismissed (Appendix B: Screenshot of the debrief page in the experiment)

High reliability rates were found for the measure of *user satisfaction with the system process*, *user satisfaction with the system outcome*, the *intention to return*, and *perceived usefulness*. The reliability coefficient alpha for *user satisfaction with the system process* is 0.95(questionnaire items 1-4), *user satisfaction with the system outcome* 0.96 (questionnaire item 11-13), *intention to return* 0.95 (questionnaire item 14-16), and *perceived usefulness* 0.97 (questionnaire item 7-10). From Rotated Component Matrix (Table 9 Factor Analysis), we can see that the alpha values in the shaded cells are visibly correlated with each other (convergent validity) and at the same time different from values in non-shaded cells of the same column (discriminant validity). Therefore, the four constructs are adequately internally consistent and externally distinctive.

Table 9 Factor Analysis

Rotated Component Matrix(a)

	Component			
	SatOut	Use	Return	SatPro
satisfaction1	.336	.337	.513	.648
satisfaction2	.405	.378	.421	.642
satisfaction3	.265	.534	.438	.581
satisfaction4	.573	.386	.168	.637
RETURN1	.392	.468	.667	.301
RETURN2	.328	.401	.631	.486
RETURN3	.441	.304	.741	.286
PERUSE1	.343	.720	.401	.359
PERUSE2	.452	.737	.300	.323
PERUSE3	.385	.601	.432	.484
PERUSE4	.493	.574	.417	.431
SatOutcome1	.697	.321	.454	.367
SatOutcome2	.701	.405	.437	.301
SatOutcome3	.800	.310	.311	.279

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
a Rotation converged in 9 iterations.

Product knowledge was calculated by standardizing and summing the four items discussed in section 6.3 (reliability coefficient alpha = 0.81). Participants were classified as either higher or lower knowledge based on a median split of the combined knowledge scores. 45 out of 90 participants were classified as lower-knowledge based, and the other half as higher-knowledge based. Means for higher- and lower-knowledge participants on these four knowledge measures were 1.42 and 2.49 for computer skills, 0.91 and 2.22 for notebook knowledge, 1.60 and 3.16 for actual notebook use, 2.06 and 4.73 years for notebook experience. The product knowledge is measured before assigning participants to different systems (Appendix B: Screenshot of the demographic form in the experiment, item 3-6). If not, the notebook information presented in the system might have biased the participants' self-assessments of their product knowledge.

Finally, ninety records were complete and usable for the data analysis. The age range of the participants was from 20 to 41, with the average of 28.5, and there are 39 females and 51 males. Of 90 participants, 27 (30%) was assigned to the catalog-based system; 36 (40%) to the DSS prototype with hierarchical clustering; 27 (30%) to the DSS prototype with nearest-neighbor clustering (Appendix D: Pie-chart of percentage of participants in each system). The ANOVA table for mean comparison (Table 10 and Table 11: Mean comparison between catalog-based system and DSS systems) shows that user satisfaction with the system process, satisfaction with the system outcome, the intention to return, and perceived usefulness for DSS users are significantly higher than that for catalog-based users; while the difference between the two DSS prototypes is trivial. Therefore, hypotheses H1a and H1b are both supported.

Table 10 Mean comparison between catalog-based system and DSS systems (ANOVA Table)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MSATP	Between Groups	133.118	2	66.559	39.968	.000
	Within Groups	144.880	87	1.665		
	Total	277.997	89			
MRET	Between Groups	127.877	2	63.938	36.115	.000
	Within Groups	154.026	87	1.770		
	Total	281.902	89			
MUSE	Between Groups	142.230	2	71.115	33.700	.000
	Within Groups	183.593	87	2.110		
	Total	325.822	89			
MSATO	Between Groups	115.593	2	57.797	25.809	.000
	Within Groups	194.831	87	2.239		
	Total	310.425	89			

Table 11 Mean comparison between catalog-based system and DSS systems (Multiple Comparisons)

Multiple Comparisons

Bonferroni

Dependent Variable	(I) systemtype	(J) systemtype	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
MSATP	0	1	-2.6296*	.32853	.000	-3.4316	-1.8276
		2	-2.6852*	.35122	.000	-3.5426	-1.8278
	1	0	2.6296*	.32853	.000	1.8276	3.4316
		2	-.0556	.32853	1.000	-.8576	.7464
	2	0	2.6852*	.35122	.000	1.8278	3.5426
		1	.0556	.32853	1.000	-.7464	.8576
MRET	0	1	-2.7006*	.33875	.000	-3.5275	-1.8737
		2	-2.4444*	.36213	.000	-3.3285	-1.5604
	1	0	2.7006*	.33875	.000	1.8737	3.5275
		2	.2562	.33875	1.000	-.5708	1.0831
	2	0	2.4444*	.36213	.000	1.5604	3.3285
		1	-.2562	.33875	1.000	-1.0831	.5708
MUSE	0	1	-2.7963*	.36983	.000	-3.6991	-1.8935
		2	-2.6667*	.39537	.000	-3.6318	-1.7015
	1	0	2.7963*	.36983	.000	1.8935	3.6991
		2	.1296	.36983	1.000	-.7732	1.0324
	2	0	2.6667*	.39537	.000	1.7015	3.6318
		1	-.1296	.36983	1.000	-1.0324	.7732
MSATO	0	1	-2.4938*	.38098	.000	-3.4239	-1.5638
		2	-2.4444*	.40729	.000	-3.4387	-1.4502
	1	0	2.4938*	.38098	.000	1.5638	3.4239
		2	.0494	.38098	1.000	-.8807	.9794
	2	0	2.4444*	.40729	.000	1.4502	3.4387
		1	-.0494	.38098	1.000	-.9794	.8807

*. The mean difference is significant at the .05 level.

We also included two additional items in the questionnaire (Appendix C, item 5 and 6) to see if the users perceived the divergence/convergence dynamics in DSSs, and the results (Table 12 and Table 13: Mean comparison for Perceived divergence/convergence dynamics) show that the DSS users certainly noticed the diversity in the alternative suggestions more than the catalog-based system users did.

Table 12 Mean comparison for Perceived divergence/convergence dynamics (ANOVA Table)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
perceived1	Between Groups	148.196	2	74.098	36.074	.000
	Within Groups	178.704	87	2.054		
	Total	326.900	89			
perceived2	Between Groups	93.113	2	46.556	19.985	.000
	Within Groups	202.676	87	2.330		
	Total	295.789	89			

Table 13 Mean comparison for Perceived divergence/convergence dynamics (Multiple Comparisons)

Multiple Comparisons

Bonferroni

Dependent Variable	(I) systemtype	(J) systemtype	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
perceived1	0	1	-2.76*	.365	.000	-3.65	-1.87
		2	-2.85*	.390	.000	-3.80	-1.90
	1	0	2.76*	.365	.000	1.87	3.65
		2	-.09	.365	1.000	-.98	.80
	2	0	2.85*	.390	.000	1.90	3.80
		1	.09	.365	1.000	-.80	.98
perceived2	0	1	-2.27*	.389	.000	-3.22	-1.32
		2	-2.15*	.415	.000	-3.16	-1.13
	1	0	2.27*	.389	.000	1.32	3.22
		2	.12	.389	1.000	-.83	1.07
	2	0	2.15*	.415	.000	1.13	3.16
		1	-.12	.389	1.000	-1.07	.83

*. The mean difference is significant at the .05 level.

Moreover, the results revealed that, in general, customer's product knowledge plays a significant role in determining customers' satisfaction with the system process and their perceived system usefulness (Table 14 and Table 15: Product Knowledge effects on all systems).

Table 14 Product Knowledge effects on ALL systems (0 – lower knowledge; 1 – higher knowledge)

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
MSATP	0	45	5.2944	1.33175	.19853	4.8943	5.6945	1.25	7.00
	1	45	4.2167	1.98760	.29629	3.6195	4.8138	1.00	6.75
	Total	90	4.7556	1.76736	.18630	4.3854	5.1257	1.00	7.00
MRET	0	45	5.2370	1.36260	.20312	4.8277	5.6464	1.00	7.00
	1	45	4.1926	1.99809	.29786	3.5923	4.7929	1.00	7.00
	Total	90	4.7148	1.77973	.18760	4.3421	5.0876	1.00	7.00
MUSE	0	45	5.4222	1.37430	.20487	5.0093	5.8351	1.00	7.00
	1	45	4.2667	2.19853	.32774	3.6062	4.9272	1.00	7.00
	Total	90	4.8444	1.91335	.20169	4.4437	5.2452	1.00	7.00
MSATO	0	45	5.1111	1.62990	.24297	4.6214	5.6008	1.00	7.00
	1	45	4.3259	2.02071	.30123	3.7188	4.9330	1.00	7.00
	Total	90	4.7185	1.86760	.19686	4.3274	5.1097	1.00	7.00

Table 15 Product Knowledge effects on all systems (ANOVA Table)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MSATP	Between Groups	26.136	1	26.136	9.132	.003
	Within Groups	251.861	88	2.862		
	Total	277.997	89			
MRET	Between Groups	24.544	1	24.544	8.393	.005
	Within Groups	257.358	88	2.925		
	Total	281.902	89			
MUSE	Between Groups	30.044	1	30.044	8.939	.004
	Within Groups	295.778	88	3.361		
	Total	325.822	89			
MSATO	Between Groups	13.872	1	13.872	4.116	.045
	Within Groups	296.553	88	3.370		
	Total	310.425	89			

The mean comparison indicates that, concerning all three systems, our participants with higher product knowledge would have lower satisfaction with system process, lower satisfaction with system outcome, lower intention to return, and lower perceived system usefulness. However, further data analysis shows that this difference only happens within the participant group of the catalog-based system users but not in that of the DSS users (Table 16 and Table 17: Product Knowledge effects on catalog-based system; Table 18 and Table 19: Product Knowledge effects on DSS systems). Therefore, hypotheses H2a and H2b are not supported.

Table 16 Product Knowledge effects on Catalog-based system (0 – lower knowledge; 1 – higher knowledge)

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
MSATP	0	9	4.3056	1.69456	.56485	3.0030	5.6081	1.25	6.25
	1	18	2.1944	1.32442	.31217	1.5358	2.8531	1.00	5.50
	Total	27	2.8981	1.74898	.33659	2.2063	3.5900	1.00	6.25
MRET	0	9	4.2222	1.46249	.48750	3.0980	5.3464	1.00	6.00
	1	18	2.2407	1.49861	.35323	1.4955	2.9860	1.00	6.33
	Total	27	2.9012	1.74144	.33514	2.2123	3.5901	1.00	6.33
MUSE	0	9	4.8056	1.58498	.52833	3.5872	6.0239	1.00	6.25
	1	18	1.9861	1.37593	.32431	1.3019	2.6703	1.00	5.50
	Total	27	2.9259	1.96093	.37738	2.1502	3.7016	1.00	6.25
MSATO	0	9	4.0741	1.76995	.58998	2.7136	5.4346	1.00	6.00
	1	18	2.4444	1.80051	.42438	1.5491	3.3398	1.00	7.00
	Total	27	2.9877	1.92261	.37001	2.2271	3.7482	1.00	7.00

Table 17 Product Knowledge effects on Catalog-based system (ANOVA Table)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MSATP	Between Groups	26.741	1	26.741	12.663	.002
	Within Groups	52.792	25	2.112		
	Total	79.532	26			
MRET	Between Groups	23.558	1	23.558	10.652	.003
	Within Groups	55.290	25	2.212		
	Total	78.848	26			
MUSE	Between Groups	47.696	1	47.696	22.807	.000
	Within Groups	52.281	25	2.091		
	Total	99.977	26			
MSATO	Between Groups	15.934	1	15.934	4.969	.035
	Within Groups	80.173	25	3.207		
	Total	96.107	26			

Table 18 Product Knowledge effects on DSS systems (0 – lower knowledge; 1 – higher knowledge)

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
MSATP	0	36	5.5417	1.12202	.18700	5.1620	5.9213	2.50	7.00
	1	27	5.5648	.90563	.17429	5.2066	5.9231	3.50	6.75
	Total	63	5.5516	1.02701	.12939	5.2929	5.8102	2.50	7.00
MRET	0	36	5.4907	1.23053	.20509	5.0744	5.9071	1.67	7.00
	1	27	5.4938	.94449	.18177	5.1202	5.8675	2.00	7.00
	Total	63	5.4921	1.10855	.13966	5.2129	5.7712	1.67	7.00
MUSE	0	36	5.5764	1.29535	.21589	5.1381	6.0147	1.50	7.00
	1	27	5.7870	.96999	.18667	5.4033	6.1708	2.75	7.00
	Total	63	5.6667	1.16311	.14654	5.3737	5.9596	1.50	7.00
MSATO	0	36	5.3704	1.50929	.25155	4.8597	5.8810	1.33	7.00
	1	27	5.5802	.84019	.16169	5.2479	5.9126	3.33	7.00
	Total	63	5.4603	1.26211	.15901	5.1425	5.7782	1.33	7.00

Table 19 Product Knowledge effects on DSS systems (ANOVA Table)

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
MSATP	Between Groups	.008	1	.008	.008	.930
	Within Groups	65.387	61	1.072		
	Total	65.395	62			
MRET	Between Groups	.000	1	.000	.000	.991
	Within Groups	76.190	61	1.249		
	Total	76.190	62			
MUSE	Between Groups	.685	1	.685	.502	.481
	Within Groups	83.190	61	1.364		
	Total	83.875	62			
MSATO	Between Groups	.680	1	.680	.423	.518
	Within Groups	98.082	61	1.608		
	Total	98.762	62			

The fact that higher-knowledge participants were less satisfied with the catalog-based system comparing to lower-knowledge participants is probably due to the possible high correlation between the user's knowledge of notebook computers and the user's knowledge of computer support systems. The participants with higher computer skills, higher notebook knowledge, experience, and usage are likely to be more exposed and experienced with advanced computer support systems, and therefore less satisfied with the simple traditional catalog system. However, the difference in satisfaction between higher and lower knowledge groups is not significant within the user group of both/any of our DSS systems, which implies that our proposed systems are equally helpful and effective to both the lower knowledge users and higher knowledge users. It is encouraging that higher knowledge users also find our systems effective, although our systems are initially aiming to assist with infrequently shopped items and their customers who have inadequate product knowledge, imprecise product preferences, and vague shopping goals. The opportunity of browsing diverse alternative solutions offered by our systems seems to be equally appealing to users with all levels of product knowledge. The overall results of the experiment are in favor of our proposed methods compared to traditional catalog method.

7 Conclusions

In this paper, we have targeted the infrequently shopped products as an ill-defined problem solving area that needs decision support applications for e-commerce customers. We promoted the divergence decision support in the scenario of infrequent purchases, and we advocated the importance of allowing imprecise user preferences in the supporting systems. Our approach combines divergent browsing and imprecise searching which are both important in pre-purchase online information seeking (Detlor et al., 2003). Our system incorporated fuzzy algorithm for users to imprecisely express their preferences. In the decision support process of our system, we also employed the well-known divergence-convergence principle in problem solving in order to suggest diverse alternatives; Cluster Analysis techniques were used to generate these diverse alternatives. Finally, an experiment was administered to test the effectiveness of our prototype systems for notebook selection. The results supported our divergence DSSs over the traditional catalog-based system in terms of users' satisfaction with system process, satisfaction with system outcome, their intention to return, and the perceived usefulness of the system.

The limitation of the study includes the nature of prototype systems. For the future research and experiments, more realistic e-commerce shopping interfaces and more browsing and searching capabilities should be incorporated in both the control system and the DSSs; however, caution has to be made so as to avoid confounded errors. Moreover, more thorough literature review in DSS, e-commerce, and marketing is required; statistical hypotheses are needed to develop a set of measures to test and guide the development of DSS for e-commerce customers. The perceptive measures that would be taken into account are user satisfaction, shopping enjoyment, intention to return, product knowledge, and arguably trust.

Trust is essentially important in building relationships with e-commerce customers. According to macKnight and Chervany (2001, 2002), trust assumes multiple meanings, which include trust on the information provided by the merchant. Sultan et al. (2002) also noted that information and advices would have positive influence on the customer's trust level, for example, the customer would trust a sales person who could communicate in his/her level of knowledge. Kim and Benbasat (2003), on the other hand, suggested that incorrect advices provided by the seller would lower customer's trust.

We believe that our approach of divergent browsing and imprecise preference expression would bring a positive influence on customer's trust. The imprecise preference expression would allow the system communicate in customer's level of knowledge. Moreover, the divergent presentation of the alternatives would reinforce customer's impression that the seller is truly trying to help him/her find the best product, rather than trying to manipulate the top recommendation list to sell certain items. Overall, the results are encouraging, and we believe that the application of our method in commercial websites is promising.

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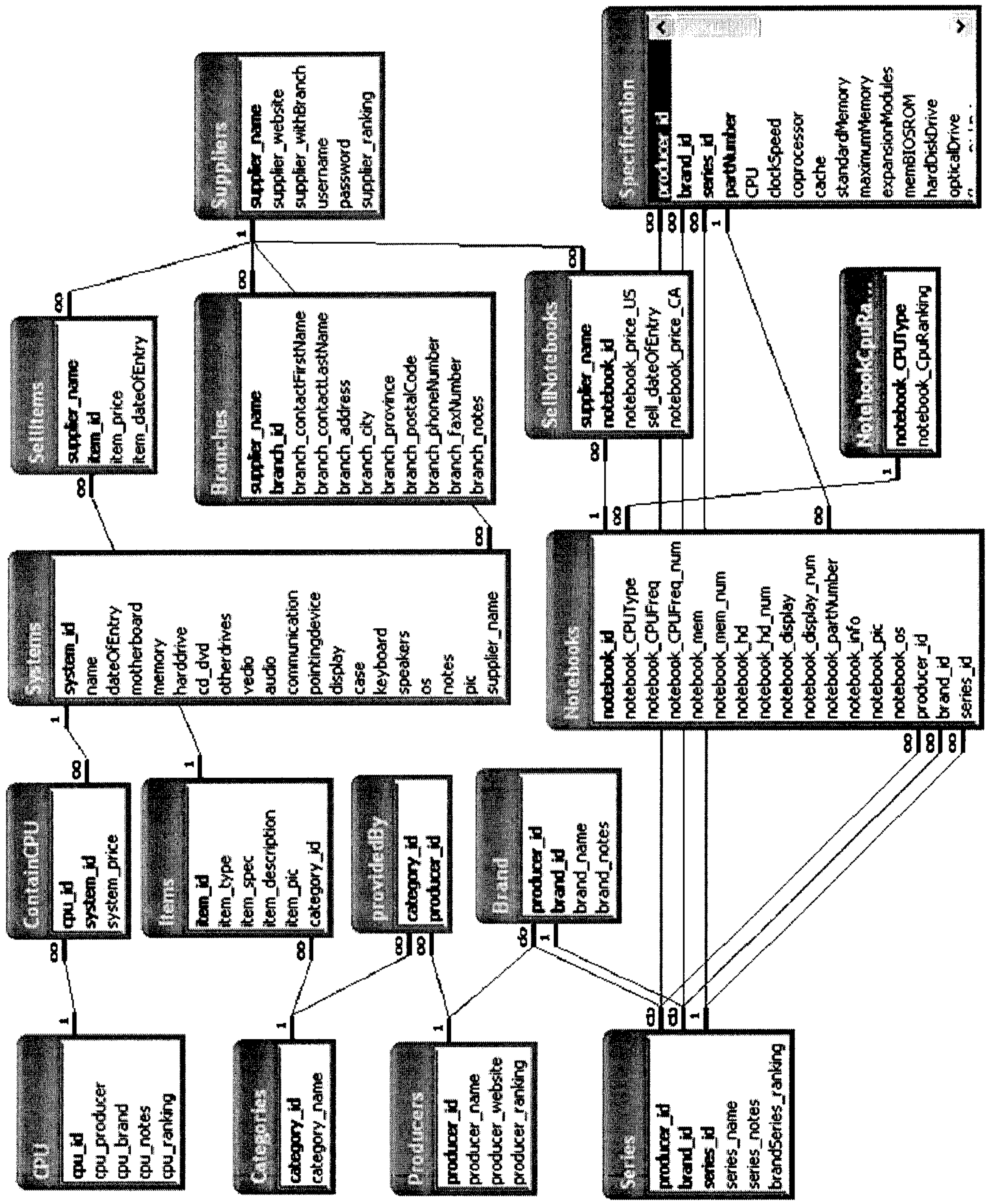
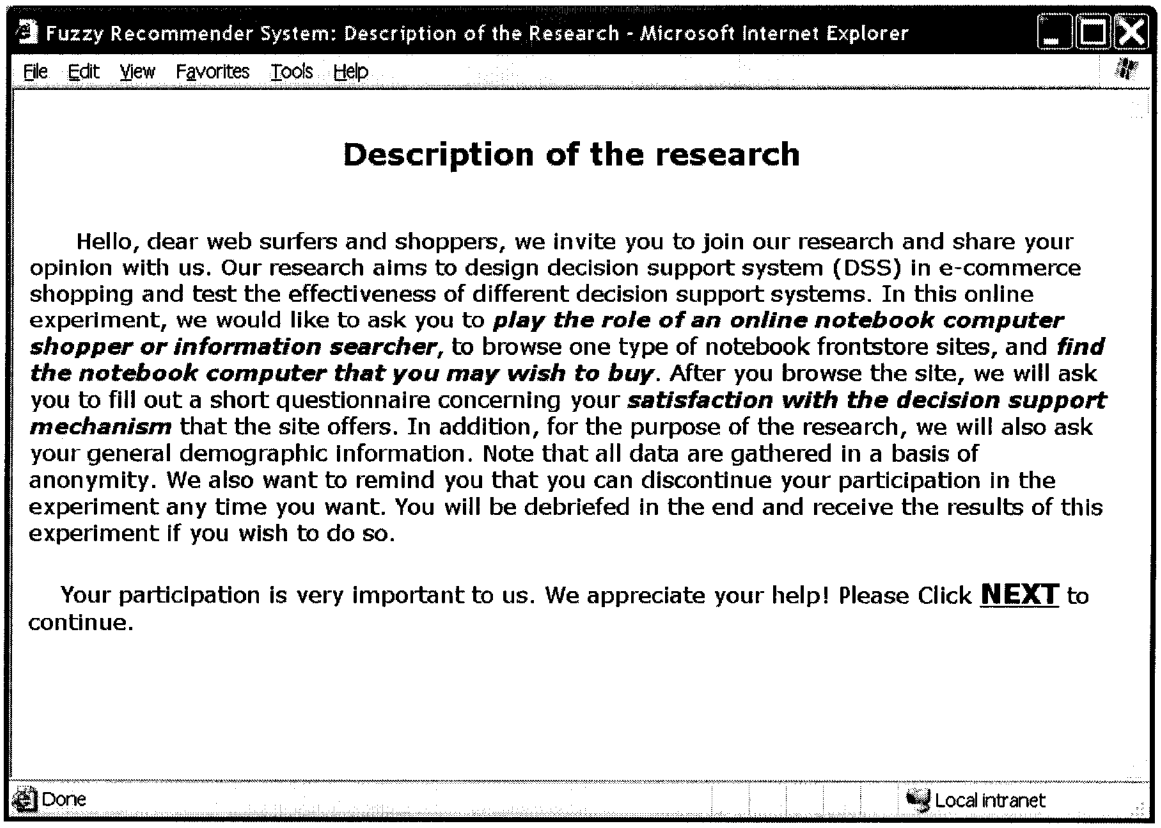
Appendix A: The relationship diagram of the database design.

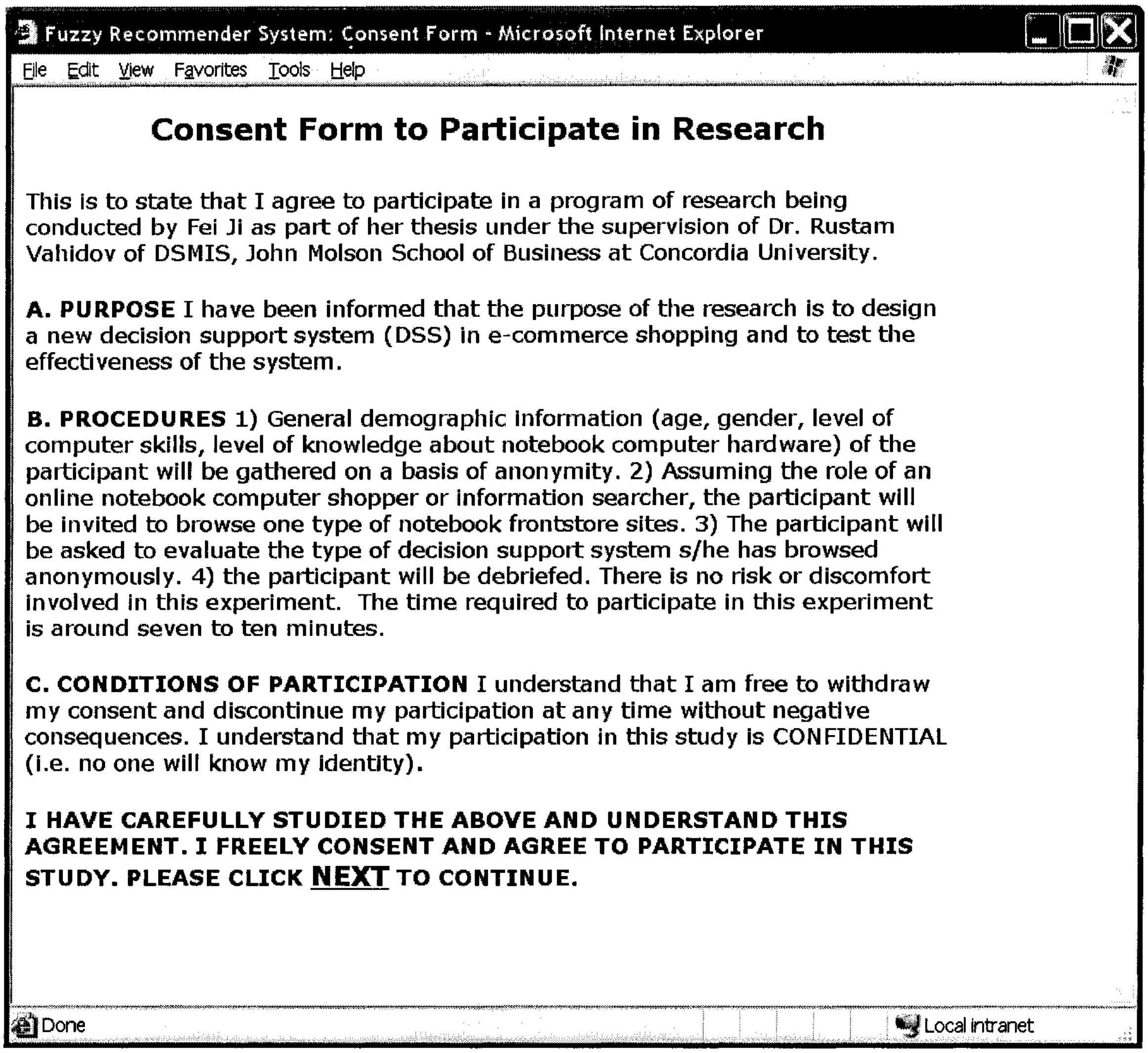


Appendix B: Experiment screenshots

Screenshot of the description page in the experiment



Screenshot of the consent form in the experiment



Fuzzy Recommender System: Consent Form - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Consent Form to Participate in Research

This is to state that I agree to participate in a program of research being conducted by Fei Ji as part of her thesis under the supervision of Dr. Rustam Vahidov of DSMIS, John Molson School of Business at Concordia University.

A. PURPOSE I have been informed that the purpose of the research is to design a new decision support system (DSS) in e-commerce shopping and to test the effectiveness of the system.

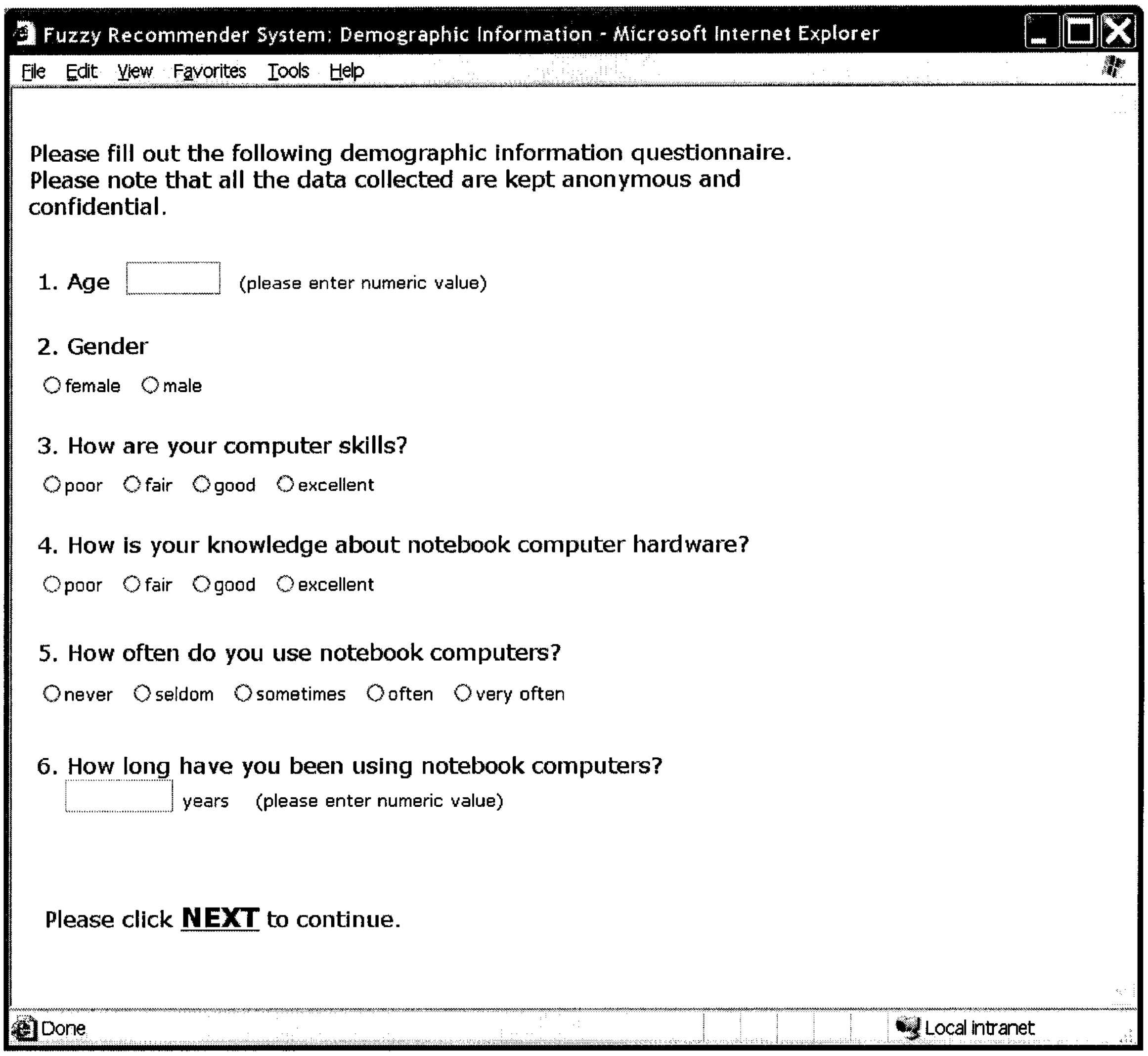
B. PROCEDURES 1) General demographic information (age, gender, level of computer skills, level of knowledge about notebook computer hardware) of the participant will be gathered on a basis of anonymity. 2) Assuming the role of an online notebook computer shopper or information searcher, the participant will be invited to browse one type of notebook frontstore sites. 3) The participant will be asked to evaluate the type of decision support system s/he has browsed anonymously. 4) the participant will be debriefed. There is no risk or discomfort involved in this experiment. The time required to participate in this experiment is around seven to ten minutes.

C. CONDITIONS OF PARTICIPATION I understand that I am free to withdraw my consent and discontinue my participation at any time without negative consequences. I understand that my participation in this study is CONFIDENTIAL (i.e. no one will know my identity).

I HAVE CAREFULLY STUDIED THE ABOVE AND UNDERSTAND THIS AGREEMENT. I FREELY CONSENT AND AGREE TO PARTICIPATE IN THIS STUDY. PLEASE CLICK NEXT TO CONTINUE.

Done Local intranet

Screenshot of the demographic form in the experiment



Fuzzy Recommender System: Demographic Information - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Please fill out the following demographic information questionnaire.
Please note that all the data collected are kept anonymous and confidential.

1. Age (please enter numeric value)

2. Gender

○ female ○ male

3. How are your computer skills?

○ poor ○ fair ○ good ○ excellent

4. How is your knowledge about notebook computer hardware?

○ poor ○ fair ○ good ○ excellent

5. How often do you use notebook computers?

○ never ○ seldom ○ sometimes ○ often ○ very often

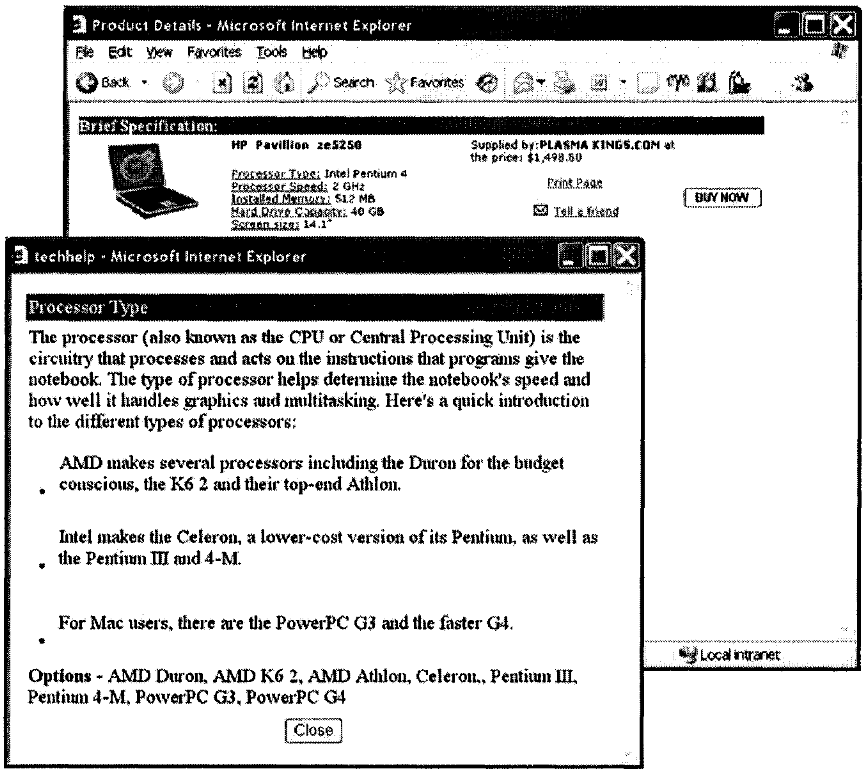
6. How long have you been using notebook computers?

years (please enter numeric value)

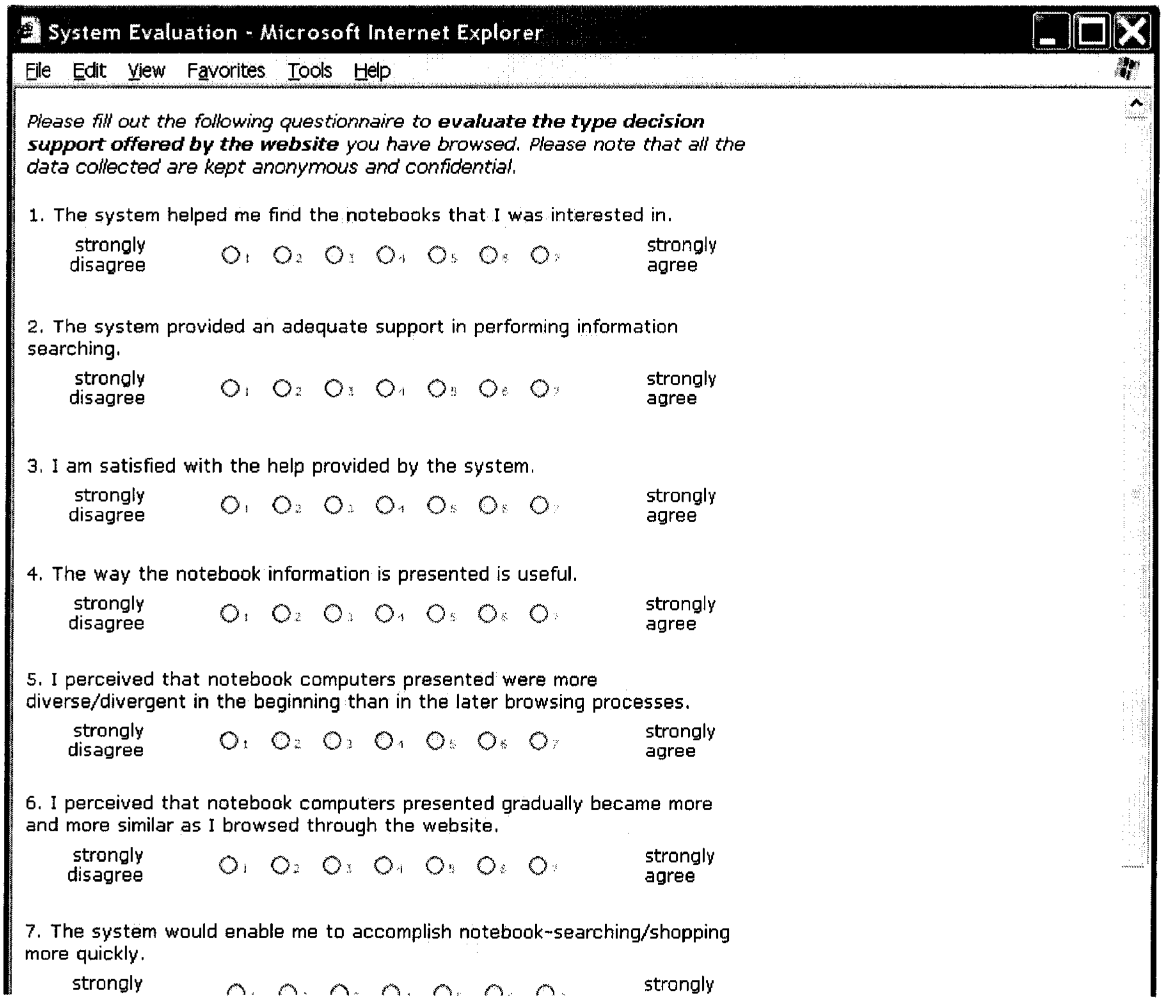
Please click **NEXT** to continue.

Done Local intranet

Screenshot of the product page in the experiment



Screenshot of the questionnaire page in the experiment



System Evaluation - Microsoft Internet Explorer

File Edit View Favorites Tools Help

Please fill out the following questionnaire to ***evaluate the type decision support offered by the website*** *you have browsed. Please note that all the data collected are kept anonymous and confidential.*

1. The system helped me find the notebooks that I was interested in.

strongly disagree ○1 ○2 ○3 ○4 ○5 ○6 ○7 strongly agree

2. The system provided an adequate support in performing information searching.

strongly disagree ○1 ○2 ○3 ○4 ○5 ○6 ○7 strongly agree

3. I am satisfied with the help provided by the system.

strongly disagree ○1 ○2 ○3 ○4 ○5 ○6 ○7 strongly agree

4. The way the notebook information is presented is useful.

strongly disagree ○1 ○2 ○3 ○4 ○5 ○6 ○7 strongly agree

5. I perceived that notebook computers presented were more diverse/divergent in the beginning than in the later browsing processes.

strongly disagree ○1 ○2 ○3 ○4 ○5 ○6 ○7 strongly agree

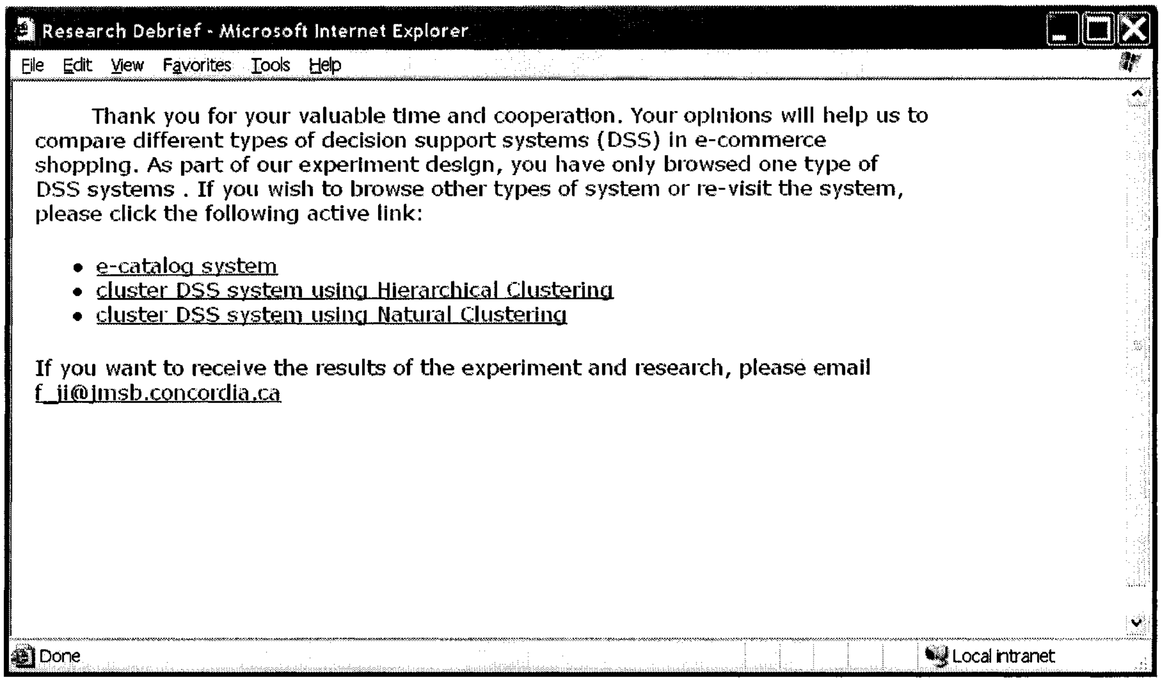
6. I perceived that notebook computers presented gradually became more and more similar as I browsed through the website.

strongly disagree ○1 ○2 ○3 ○4 ○5 ○6 ○7 strongly agree

7. The system would enable me to accomplish notebook-searching/shopping more quickly.

strongly strongly

Screenshot of the debrief page in the experiment



Appendix C: Questionnaire

1. The system helped me find the notebooks that I was interested in.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
2. The system provided an adequate support in performing information searching.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
3. I am satisfied with the help provided by the system.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
4. The way the notebook information is presented is useful.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
5. I perceived that notebook computers presented were more diverse/divergent in the beginning than in the later browsing processes.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
6. I perceived that notebook computers presented gradually became more and more similar as I browsed through the website.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
7. The system would enable me to accomplish notebook-searching/shopping more quickly.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
8. The system would enhance my effectiveness on searching/shopping for notebooks.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
9. The system would make it easier for me to search/shop for notebooks.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
10. I would find the system useful in my searching/shopping for notebooks.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree
11. the search results meet my expectations.
strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree

12. I am satisfied with the search outcome.

strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree

13. The system output was comprehensive.

strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree

14. If you had a future need for information/service presented in this website, how likely is it that you would consider returning/using the website with this kind of decision support system?

very unlikely – 1 – 2 – 3 – 4 – 5 – 6 – 7 – very likely

15. I intend to browse the website with this type of decision support system again in the near future if I need information/service presented in this website.

strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree

16. I intend to browse the website with this type of decision support system frequently in the future.

strongly disagree – 1 – 2 – 3 – 4 – 5 – 6 – 7 – strongly agree

Appendix D: Experiment Results

Pie-chart of percentage of participants in each system