An Adaptive Product Recommendation System for Anonymous Internet Visitors

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Abstract

This research develops an adaptive product recommendation system for anonymous new customers based on their interests, media preferences, and the Web page downloading time. To protect the user's privacy, a temporary user model is constructed when the user enters the system and deleted when the user leaves, so the user remains anonymous throughout the browsing session. The system can estimate the user's current interests by incremental learning by observing the user's browsing behavior. By using the exponential smoothing procedure, the user's interests are estimated smoothly by increasing the weight of more recent selected information so that the system can track incremental change of user interests. For the issue of system performance, a two-layer product catalog structure and a two-stage breadth-first search algorithm are proposed to reduce system load so that the possibility of real-time recommendation is increased. In addition, this system uses a frame variant based dynamic Web page to adaptively present the product data with respect to the user's media preference and the Web page downloading time to increase the user's will to continue browsing on the Web site.

An experimental system for recommending audio CDs was developed and a TAM model was used to evaluate the proposed adaptive product recommendation system. The experimental results revealed that the perceived ease of use and usefulness of the proposed system had significant positive effects on the user's attitude and intention to use the proposed system. For perceived ease of use, perceived usefulness, and attitude to use, there were no significant difference between high bandwidth and low bandwidth users. However, the low bandwidth users had higher intention to use the proposed system. In addition, the experimental results revealed that the subjects believed that the experimental system could recommend audio CDs they were interested in and they would be willing to use the experimental system, especially when their needs were not clear. This implies that the proposed model can be especially beneficial for those users who do not know their real needs and/or do not know how to clearly specify their needs. The subjects also agreed that the experimental system could provide graphics and audio clips matching the bandwidth they used. For system efficiency, the subjects agreed that the experimental system could help them quickly find audio CDs of interest to them.

Keywords: adaptive Web site, user model, privacy, product recommendation, anonymous user

1. Introduction

With the rapid expansion of the Internet, electronic commerce (EC) is increasingly competitive, so effective communication with customers is becoming the key to success. Being the major interface for customer communication, a firm's Web site not only provides product specifications to customers but also serves as an important channel for customer service. However, for Web sites with large amounts of information, the problems of "information overload" and "disorientation" increase the difficulties of decision-making for the customers who are not familiar with the Web site structure or with the product properties. Therefore, a successful EC model not only needs to provide high quality products with low prices but also must actively help the user for information retrieval, needs identification, product selection, and product purchase. To this end, personalization is indispensable for modern EC Web sites.

As directed by the Web site, personalization provides personalized information by automatically improving organization and presentation of a Web page by learning from user browsing patterns to achieve personalized services (Perkowitz and Etzioni, 2000). An adaptive Web-based system is very useful for personalization. From the user's point of view, an adaptive Web-based system can help the user overcome problems of information overload and disorientation, which often occur while browsing. Furthermore, from the information provider's point of view, an adaptive Web-based system is helpful to deliver information to users more efficiently and effectively. Adaptation decision in adaptive Web-based systems is based on the user's characteristics as represented in the user model. Identifying the user's characteristics, therefore, is the key to developing adaptive Web-based systems.

However, in identifying user characteristics, most systems face the following problems:

(1) Users are not motivated to answer questions and they are often reluctant to give personal information, so they are less willing to use such systems (Koychev and Schwab, 2000);
(2) Users may not clearly know their own needs or how to specify the keywords for searching;
(3) Users' interests may change over time, and sometimes even during the browsing context in the same session (Hirashima et al., 1998);
(4) Learning the users' interests by mining from historical data of users requires a huge amount of data so that it is inapplicable initially and for those sites without enough user data;
(5) Keeping, monitoring, and recording users' browsing behaviors may result in the problem of user privacy (Kobsa, 2002); and
(6) Personalized services are not applicable for new visitors to those personalization Web sites developed for "old" customers.

It is assumed that the behavior of customers can be dependent on customer preferences for a special type of medium and media downloading time; and that the actual situation can change with time (Joerding, 1999). However, most studies of adaptive Web-based systems focus on adapting to user features such as the user's goals/tasks, knowledge, background, hyperspace experience, preference, and interests (Brusilovsky, 2001). Few adaptive Web sites provide product recommendation based on the user's media preferences. Furthermore, media downloading time may be so long that it reduces the user's interest in browsing. To this end, this research proposes an adaptive product recommendation system aimed at anonymous new users to achieve the following goals:

(1) An adaptive product recommendation system that protects the user's privacy;
(2) An adaptive product recommendation system that deduces the user's interests without asking the user to answer questions;
(3) An adaptive product recommendation system that is able to deduce the user's interests for those users who do not clearly know their own needs or how to specify the keywords for searching;
(4) An adaptive product recommendation system that reflects changes in the user's interests; and
(5) An adaptive product recommendation system that adaptively presents the product data to users based on their media preferences and the Web page downloading time.

The structure of this paper is: in Section 2 related literatures are reviewed; the architecture of the proposed adaptive product recommendation system is discussed in Sections 3; in Section 4, an experimental system is proposed to evaluate the proposed system; and Section 5 concludes this paper.

2. Literature Review

This section reviews literature related to this research. Section 2.1 reviews issues of presenting products to customers through the Internet; in Section 2.2, issues of adaptive Web-based systems are discussed; and Section 2.3 concludes this review.

2.1 Presenting Products to Customers through WWW

Within a technology-mediated customer experience, the customer's interaction with the company is not the "face-to-face" encounter in a traditional retail environment, but rather a "face-to-screen" interface. Thus it is important to consider the types of interface design. Electronic catalogs (e-catalogs), which are electronic representations of product information, comprise the major interface between customers and the company. An e-catalog is a Web-based application that serves as the front-end to provide the company with a new channel to market, sell, and support its products. The most important characteristic of e-catalogs is they can be seamlessly integrated with other functions of the company and of its business partners. From the customer's point of view, it offers an alternative means of finding out what products are currently available, who the suppliers are, and how to get such products (Segev et al., 1995). E-catalogs are often information-intensive. Their primary purpose is to increase awareness of the company and its product and services, and develop a closer customer relationship.

It is important to give customers alternative ways within a Web site to find products (Schneider and Perry, 2000, p. 111). However, many e-catalogs are static and passively present product information to customers. Web sites with static e-catalogs can only provide static listings of products and cannot respond to the customer preferences and personal characteristics. E-catalogs that are dynamic, active, and capable of learning would be ideal for business-to-consumer (B2C) Web sites (Baron et al., 2000). One key feature the e-catalog designers need to consider is how to implement personalized services by understanding the customer's personal interests and characteristics. How to present the product information with respect to personal characteristics, hence, is one of the key issues for e-catalogs.

People seldom visit a Web site by accident; they are there for a reason. Businesses realize that every visitor to their Web sites is a potential customer. An important Internet marketing goal when building a Web site is to consider these visitor characteristic variations so that visitors can be converted into customers. However, creating a Web site that meets the needs of visitors can be challenging. Web site visitors arrive with not only different needs but also different characteristics. Thus, an important concern for businesses crafting a Web site presence is the variation in important visitor characteristics (Schneider and Perry, 2000, p. 251).

Web sites with adaptive e-catalogs are solutions to build flexibility into Web site design, which is one of the best ways to accommodate a broad range of visitor characteristics. Most current adaptive Web-based system studies focus on adapting to user features such as goals/tasks, knowledge, background, hyperspace experience, preference, and interests (Brusilovsky, 2001). In addition to these user features, Joerding (1999) proposed that the behavior of customers can be dependent on customer preferences for special types of media and media downloading time. According to Schneider and Perry (2000, p.251), a well-designed Web site should have the following properties: (1) If rich media are used, the visitor should be given the option to select simpler versions of the media so that the page will load on a low-bandwidth connection in a reasonable amount of time. (2) The site should be able to let visitors select information attributes, such as level of detail, forms of aggregation, viewing format, and downloading format. (3) It should be able to offer visitors multiple information formats by including links to files in those formats. However, currently, few adaptive Web-based systems provide adaptive e-catalogs based on the visitor's media preferences and media downloading time. Therefore, one of the research goals is to develop a Web site with an adaptive e-catalog based on the visitor's media preferences and media downloading time.

2.2 Adaptive Web-Based Systems

According to Brusilovsky (1998; 2001), an adaptive Web-based system can be useful in any application area where the system is expected to be used by people with different characteristics and where the hyperspace is reasonably large. Perkowitz and Etzioni (2000) proposed that adaptive Web-based systems can automatically improve their organization and presentation by learning from user browsing patterns to achieve personalized services. De Bra (1999) suggested that the adaptive Web-based system should try to guide the user towards relevant, interesting information and away from irrelevant information or pages the user cannot understand; and that this type of system should provide additional or alternative information to ensure that the relevant information is shown and that the user can understand the information as it is presented. An adaptive Web-based system can help users obtain information according to their individual characteristics, fulfilling their real needs automatically, and also avoid the problems of information overload, disorientation, cognitive overload, discontinuous flow, content unreadiness, and lack of comprehension (Chen and Ford, 1997; Murray, Shen et al., 2000).

In general, an adaptive Web-based system includes three components: system, user data, and user model (Brusilovsky, 1998). The system is responsible for collecting user data to update the user model and adaptively recommending the next Web page content. User modeling and adaptation are the two critical tasks that integrate the three components of adaptive Web-based systems. Adaptation decision in adaptive Web-based systems is based on considering the user characteristics represented in the user model.

2.2.1 User Modeling

To develop an adaptive Web-based system for personalized service, it is necessary to obtain user data to construct the user model for adaptation. The methods for obtaining data about users can be divided into *explicit* and *implicit* approaches (Brusilovsky, 2001; Hanani et al., 2001).

2.2.1.1 Inquiring User Data Explicitly

The explicit approach is based on users voluntarily inputting their own data. Systems utilizing this method usually require their users to fill out a form to describe their interests or other relevant parameters. Some systems provide users with a predefined set of profiles from which they may select the most suitable profile. Other systems allow users to specify keywords and their weights to create their initial profiles. In a different approach, some systems do not inquire about user data in the beginning to build an initial user profile, but rather ask users to evaluate the document's relevancy as they are browsing, and based on the evaluation results, the systems build/update the user profile. Some systems ask users to input keywords directly for searching (Hanani et al., 2001).

However, users are not motivated to answer questions and they often hesitate to provide private data, so some users do not want personalized services (Joerding, 1999; Kobsa, 2002). Besides, asking users to fill out a form and/or answer questions may interrupt the browsing processes (Koychev and Schwab, 2000; Lieberman, 1995). Many users are unwilling to be interrupted during browsing even though they do know they may get an advantage over the long term. Rather, they just want to be spectators and are not willing to feedback any information to the Web site (Joerding, 1999; Kobsa, 2002; Koychev and Schwab, 2000).

In addition, to build/update the user model by explicitly asking for user data may face the following problems: (1) Users do not always know their needs clearly; (2) users may not know how to specify their needs even though they do know their needs; (3) users may have different needs at different times; and (4) users may be influenced by the content/links in the browsed information so that their interests may change during the browsing session (Lieberman, 1995). Therefore, explicitly inquiring for user data to build/update the user model may not be appropriate in some applications.

2.2.1.2 Acquiring User Data Implicitly

Some systems do not require users to input personal data, but instead acquire user data implicitly and automatically infer the user model. For this, the user's reaction to each incoming data item is recorded (Hanani et al., 2001). However, in order to proceed with long-term analysis of user behavior, many systems ask the user to input his/her personal data to build up the initial user profile. Then, based on this known user profile and the user's historical browsing records, the system implements the adaptation analysis for user interests.

The system continues monitoring and recording the user's browsing behavior during every browsing session.

As society is increasingly concerned with the user privacy and users are less willing to provide private data, hence, processing with anonymous user data is becoming more important. However, to achieve one-to-one marketing and information recommendation, many systems still try to identify who the user is, even for anonymous users. For this purpose, many systems embed mechanisms, such as cookies and tracking software agents, in the user's browser and/or record the user IP address as the user connects to the system server so that the system can identify the user when he/she connects to the system later. In this way, those systems can continue to monitor and track the user's browsing behavior over different sessions. But in reality, many users use computers in public environments, such as school or the office, so that different users may share the same computer and IP address, and the same user may use different computers and IP addresses. Moreover, not all users have static IP addresses even though they use their own computers. Therefore, collecting the user long-term behavior data by tracking software agents, cookies, and/or IP addresses might be ineffective. In addition, these methods may be in conflict with privacy concerns of users. Privacy laws protect the data of identified or identifiable individuals, and it is not required that the system actually identifies the user. Privacy laws apply when it is possible to identify the user with reasonable effort based on the data that the system has collected (Kobsa, 2002). Kobsa (2002) pointed out that privacy laws often not only affect the conditions under which personal data may be collected and the rights that data subjects have with respect to their data, but also the methods that may be used for processing this data. To this end, building a temporary user model for the anonymous user is important for adaptive web-based systems (Joerding, 1999) and is one of the goals of this research.

2.2.1.3 Inferring User Interests

Many systems determine user goals/interests based on the weights of browsed information. Hirashima et al. (1998) used an exponential formula to deduce the user interest and offer lists of most relevant links. This formula was $N_w(k) = r^{n-k}$ $(0 < r < 1)$, where, $N_w(k)$ is the weight of the k^{th} node the user visited; n is the number of nodes the user visited; and r is the ratio of decrease of user's interest. This formula considered the historical data and had the capability of fault tolerance. However, the response time might be slowed down because of the exponential calculation required, especially for large hyperspaces. In the research of Benaki, Karkaletsis, and Constantine (1998), the formula $\sum_{i=1}^{n}(\text{SourceCertainty}_i \times \text{SourceWeight}_i) / \sum_{i=1}^{n}\text{SourceWeight}_i$ was used to obtain the certainty weight ratio of the user's interest. Though not using the exponential calculation, this formula needed to sum up the weights of all nodes for every step, and as a result so the response time might also be delayed. To be more robust, the formulae become more complex and need more system resources, so they may become one of the bottlenecks of efficiency. Therefore, one of the goals of this research is to use simple formulae to improve the system efficiency in order to increase the possibility of real-time information recommendation.

Veerman (1999) summarized that there are five basic browsing strategies: scanning, browsing, searching, exploring, and wandering. Users' goals/interests may change over time as scanning, exploring, and wandering strategies are used. Especially, for wandering, there are no specific initial goals. In this case, the system may need to deduce the user's potential needs. Researchers have pointed out that indications of goals/interests should have a factor of decaying over time (Hirashima et al., 1998; Joerding, 1999; Koychev and Schwab, 2000; Lieberman, 1995). Therefore, how to increase the weight of more recent user data to adaptively estimate the user goals/interests is also one of the goals of this research.

2.2.2 Adaptation

Adaptation decisions, including adaptive link support and adaptive presentation support, in adaptive Web-based systems are based on taking into account the user characteristics represented in the user model (Brusilovsky, 1998; 2001).

2.2.2.1 Adaptive Link Support

Adaptive link support describes methods for personalizing the presentation of links based on the user characteristics, and it helps users find their paths in hyperspace (Kobsa et al., 2001). Adaptive link support techniques are used to achieve adaptation goals such as providing global guidance, providing local guidance, supporting local orientation, and supporting global orientation (Brusilovsky, 1998; 2001). The purpose of global guidance is to help the user find the shortest way to the information goal with minimal indecision. The user's information goal provided by the user is the primary feature of adaptive global guidance. Local guidance helps the user navigate by suggesting the most relevant links to follow from the current node. Local guidance does not expect a global goal to provide guidance. Instead, it makes suggestions according to the user interests, knowledge, or background. The purpose of local orientation is to help the user to understand what are the surroundings and what is his/her relative position in the hyperspace. It does not guide the user directly but provides help in understanding what are the proximal links and enables well-grounded navigation choices. Global orientation helps the user understand the structure of the overall hyperspace and his/her absolute position. In traditional non-adaptive Web-based systems, global orientation is usually achieved by providing the site map of the Web site. Adaptive Web-based systems can provide more support for global orientation by applying hiding and annotation technologies.

Techniques used for adaptive link support are shown in Figure 1 (Brusilovsky, 1998).

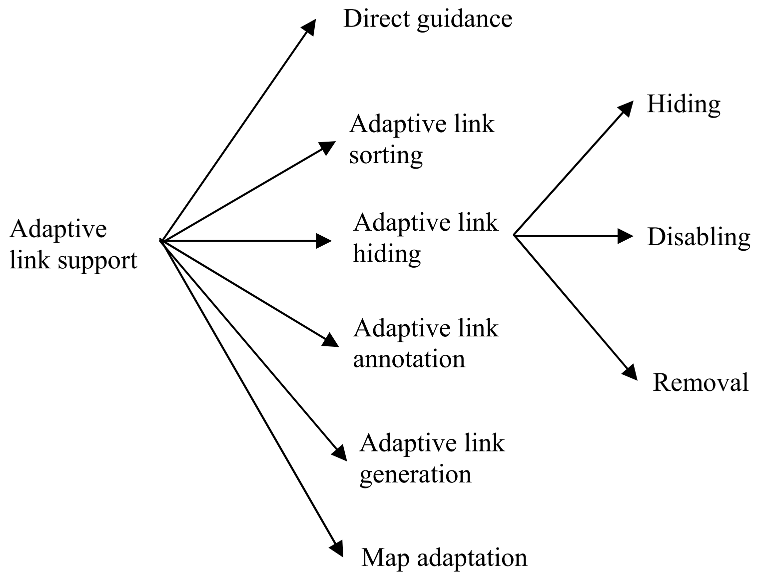


Figure 1: Adaptive link support techniques (Source: Brusilovsky, 2001)

2.2.2.2 Adaptive Presentation Support

Adaptive presentation support describes methods to personalize the content of hypermedia objects and pages in accordance with the user characteristics and/or methods, and thereby changing the presentation and media form, as well as the interaction elements (Kobsa et al., 2001). It is often used in conjunction with adaptive link support. Adaptive presentation support techniques are used to achieve adaptation goals such as additional explanations, prerequisite explanations, comparative explanations, and explanation variants (Brusilovsky, 1998). The purpose of additional explanations is to hide from the user some parts of information about a particular concept that are not relevant to his/her knowledge level about this concept. Both prerequisite explanations and comparative explanations change the information presented about a concept depending on the user knowledge level of related concepts. The difference between them is that prerequisite explanations are based on prerequisite links between concepts, whereas comparative explanations are based on similarity links between links. In addition, explanation variants assume that different users may need essentially different information. It stores several variants for some parts of the page content and the user obtains the variant based on his/her user model.

Techniques used for adaptive presentation support are shown in Figure 2 (Brusilovsky, 2001).

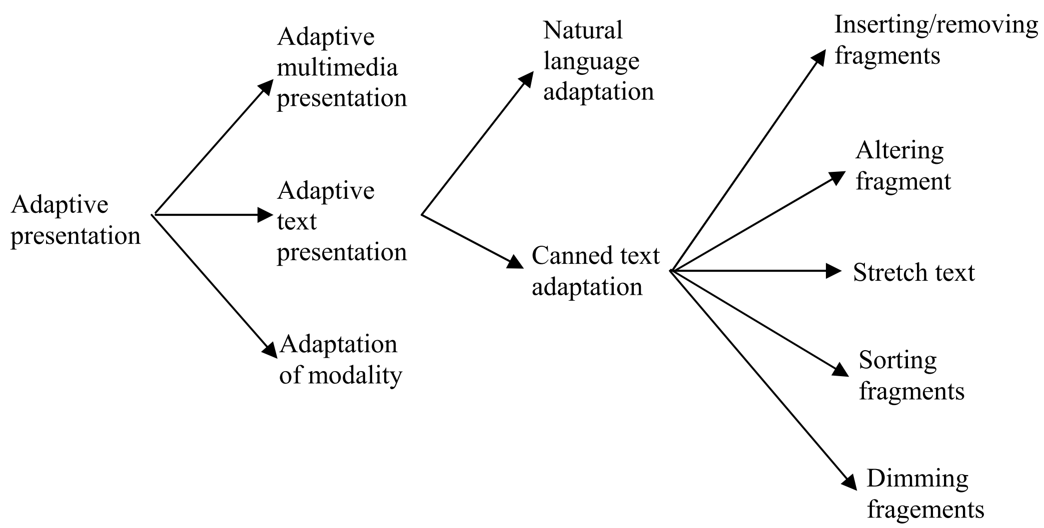


Figure 2: Adaptive presentation link techniques (Source: Brusilovsky, 2001)

Different presentation formats may have different effects for users with different media preferences. Therefore, including user media preferences in e-catalog presentation is important for one-to-one marketing. To this end, one of the goals of this research is to develop an adaptive presentation support for users with different media preferences.

According to Zona Research (1999), 30% of users will stop browsing if the Web page waiting time exceeds 8 seconds. Therefore, for e-catalog presentations, the Web page downloading time is one of the critical factors. Since the usage of multimedia files is becoming popular, if the bandwidth does not increase accordingly, the Web page downloading time might become longer, so users may more easily become impatient and leave. Therefore, adaptive presentation based on the bandwidth (Web page downloading time) is also one the goals of this research.

2.3 Summary of Literature Review

According to the above review, it may be concluded that the adaptive product recommendation system developed in this research should meet the following requirements:

(1) The adaptive product recommendation system should build a temporary user model for anonymous users to protect their privacy.
(2) The adaptive product recommendation system should use simple formulae to improve the system efficiency.
(3) The adaptive product recommendation system should increase the weight of more recent user data to deduce the user goals/interests adaptively.
(4) The adaptive product recommendation system should adaptively present the product data to users based on their media preferences and the Web page downloading time.

3. System Architecture

The proposed adaptive product recommendation system architecture is based on the client/server structure (Figure 3). Here, the user selects the product shown in Web page through the Web browser, and the motion sensor in the client then feeds this action data back to the server to update the user model for adaptation.

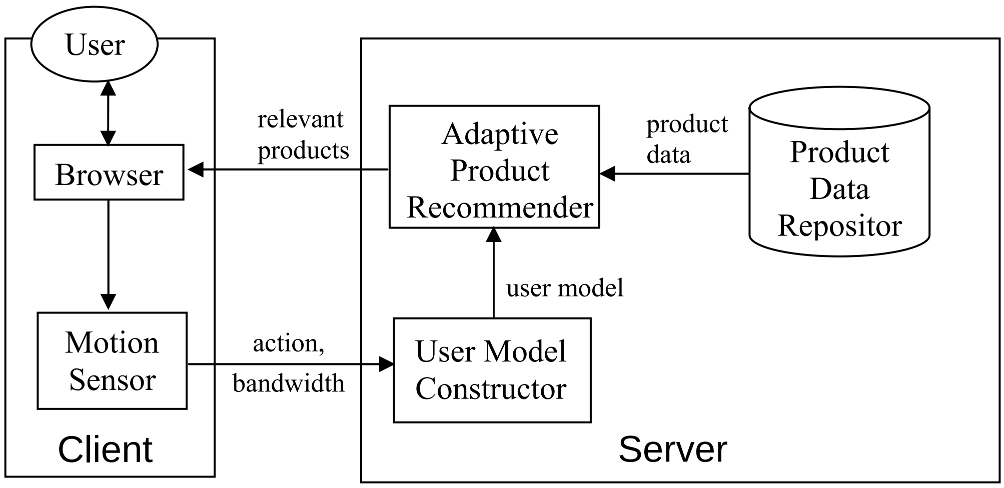


Figure 3: System architecture

There are three components in the server: *Product Data Repository*, *User Model Constructor*, and *Adaptive Product Recommender*. The *Product Data Repository* stores the product data based on the product data architecture discussed in Section 3.1. The *User Model Constructor*, together with the observed user browsing behavior, is responsible for building and updating the temporary user model for incremental learning of the user's interests (discussed in Section 3.2) and media preferences (discussed in Section 3.4). The *Adaptive Product Recommender* is responsible for determining the recommendation sequence (discussed in Section 3.3) and the presentation form (discussed in Section 3.4) of products in the *Product Data Repository* based on the user model.

3.1 Product Data Architecture

Many researchers use keyword vectors to represent product features. In a keyword vector, each keyword is assigned a weight. However, for many applications, the number of keywords could be so many that the system load is increased, thus, reducing the possibility for real-time product recommendation. In this research, a two-layer product data architecture, *category layer* (*concept layer*) and *description layer* (*keyword layer*), is proposed to facilitate the efficiency of real-time recommendation.

The category layer is used to abstractly categorize the products. The characteristics of a product category are represented by the weight distribution of *product category concept vector*, **WC**. The system can estimate product categories of possible interest to the user by observing the distribution of user's selected product categories. If a user frequently selects products under certain product categories, the system may, thus, conclude that the user is more interested in these product categories than other categories.

The description layer specifies each product under product categories according to the keyword weights. Its purpose is to clearly define the characteristics of all products in the product data repository. Each product has its own descriptive keywords and category. The *product keyword vector*, **WK**, is used to describe the characteristics of a product. A product can be clearly identified through the weights of keywords in the keyword vector.

In a concept vector **WC**, there is a set of corresponding keywords for each concept (Figure 4). Though there are many keywords in the keyword vector for the description layer, in reality not all concepts in a category have weights worthy of being noted. While implementing product recommendation, only those keywords corresponding to the concepts whose weights exceed a certain threshold shall be considered. In this way, the system load can be reduced tremendously (see Section 3.3 for detail). In the concept vector of Figure 4, *italics* indicate that the concept weights exceed the threshold, i.e., this concept is a *noteworthy concept*. In the keyword vector, *italics* indicate that the concept this keyword corresponding to is a *noteworthy concept*. Multiple concepts may share a common corresponding keyword.

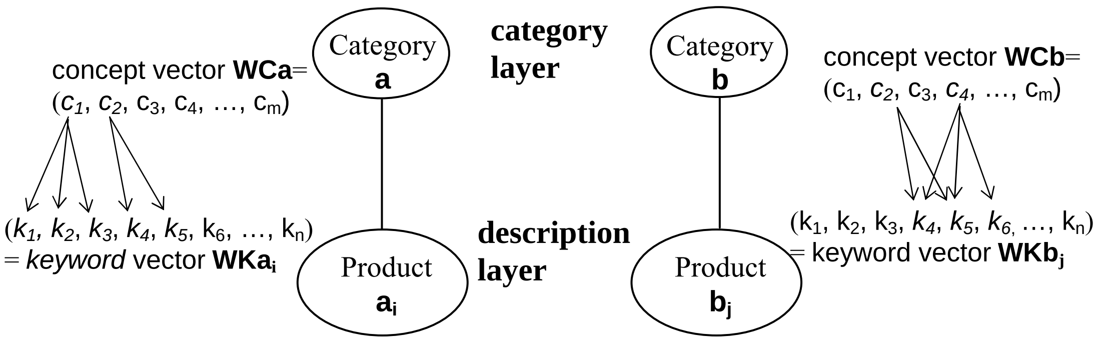


Figure 4: The product data architecture

3.2 Temporary User Model of the User's Interests

The proposed product recommendation system uses the browsing behavior of the user to deduce the user's interests. As the user enters the system, no user interests are predefined in advance; instead, the system builds a temporary user model without knowing the user's background as the *anonymous* user enters the system. The system will then deduce the user's current interests by incremental learning. To protect the user's privacy, this temporary user model will be deleted immediately after the user leaves the system and will not be used further.

While deducing the user's interests, the older the user data, the less value it has (Lieberman, 1995). The temporal effect of user data, therefore, must be considered. In this research, the temporal effect of the user's browsing actions is processed smoothly, meaning that the user model is updated gradually. The purpose of smooth processing is to allow fault-tolerance, i.e., the validity of recommendation will not be greatly affected if the user selects some unintended links by mistake. Some actions may have been highly dependent on the local context and should be neglected unless they are reinforced by another recent action (Lieberman, 1995). On the other hand, the user is possibly influenced by the content he/she has read so that the user's interest might have changed during the browsing session, i.e., the user might accidentally find products of interest on another topic (Lieberman, 1995). The system, therefore, should be able to correspondingly adjust the user's estimated interest. The proposed system updates the user model based on the recency and relevance of user actions. If the user consecutively selects relevant products, in the user model, the weights of the corresponding keywords and concepts increase. On the contrary, if the user does not consecutively select relevant products of the user's estimated interest, the weights in the user model decrease. The updating process is implemented smoothly so that the reliability and efficiency is increased.

To this end, the exponential smoothing forecasting procedure is used to update the user model (Figure 5). A user model consisting of two descriptors, *user concept vector* **UC** and *user keyword vector* **UK**, is built. Vector attributes of **UC** and **UK** are identical to those of the product category concept vector **WC** and the product keyword vector **WK**, respectively. Initially ($t = 1$), $\mathbf{UC}_1 = \mathbf{WC}_1$ and $\mathbf{UK}_1 = \mathbf{WK}_1$.

$$\mathbf{UC}_{t+1} = \alpha \cdot \mathbf{WC}_t + (1-\alpha) \cdot \mathbf{UC}_t$$

$$\mathbf{UK}_{t+1} = \beta \cdot \mathbf{WK}_t + (1-\beta) \cdot \mathbf{UK}_t$$

$\mathbf{UC}_t$ = the weights of user concept vector of the most recent time t
$\mathbf{UK}_t$ = the weights of user keyword vector of the most recent time t
$\mathbf{UC}_{t+1}$ = the predicted weights of user concept vector of the next time $t+1$
$\mathbf{UK}_{t+1}$ = the predicted weights of user keyword vector of the next time $t+1$
α = smoothing constant ($0<\alpha<1$), the extent $\mathbf{WC}_t$ influences the prediction
β = smoothing constant ($0<\beta<1$), the extent $\mathbf{WK}_t$ influences the prediction
$\mathbf{WC}_t$ = the weights of product category concept vector the user selects at the most recent time t
$\mathbf{WK}_t$ = the weights of product keyword vector the user selects at the most recent time t

Figure 5: The formulae for calculating the weights of **UC** and **UK**

The exponential smoothing is used because of the following features:

(1) The weights of **UC** and **UK** are always between 0 and 1 as long as the weights of all **WC**s and **WK**s are between 0 and 1. Therefore, normalization is not needed and the adaptation process can be implemented directly.

(2) It gives the most weight to the recent product/product categories the user has selected and decreases weights of earlier observations so that the system can estimate the user's current interests by incremental learning and possibly deduce the user's potential interests.
(3) Though called "exponential", only two multiplication operations and one addition operation are used for every step. This makes this procedure reacts more quickly than the formulae used in previous studies (e.g., Benaki et al., 1998; Hirashima et al., 1998).
(4) The word "smoothing" means that the system updates the user model gradually, so that the weights of the user model will not be suddenly changed if he/she makes mistakes. This gives the system has the better fault-tolerance ability.

3.3 Determination of Product Recommendation Order Based on User Interests

The product recommendation system suggests products related to the user's current interests based on the updated user model. In general, search methods include depth-first methods and breadth-first methods. Although it is used by many systems, the depth-first search method can be more efficient only if the product can be clearly classified in a hierarchical tree structure. However, the attributes among products, usually cannot be clearly differentiated, i.e., products may not be definitely classified into the hierarchical tree structure. The products conforming to the user's interests may be located in different branches from the branch structure designed by the system. In this case, for the depth-first method, one must return to the common parent node to explore the relevant node at the same level, which is less efficient. In addition, the user usually does not clearly know the product structure constructed in the system, so that when the user gets in a deep node, this may cause disorientation. Therefore, Lieberman (Lieberman, 1995) suggested employing a breadth-first search.

However, in general, the hyperspace may be very large and there may be thousands of keywords to specify a product. This decreases the possibility for real-time recommendation when directly using the breadth-first search method. To this end, incorporating a two-layer product data architecture discussed in Section 3.1, a two-phase breadth-first search method is developed. Vector attributes of the user concept vector **UC** and the user keyword vector **UK** in the user model are identical to those of the product category concept vector **WC** and the product keyword vector **WK** in the product data repository. We may, hence, adopt the vector space model (VSM) to retrieve the product categories and products conforming to a user's interest based on the user model.

Let the concept vector $\mathbf{C} = (c_1, c_2, \ldots, c_m)$, where c's are the concept vector attributes and m is the number of concept vector attributes; keyword vector $\mathbf{K} = (k_1, k_2, \ldots, k_n)$, where k's are the keyword vector attributes and n is the number of keyword vector attributes. In the product data repository, the product category concept vector of product category *i* is $\mathbf{WC}_i = (c_{1i}, c_{2i}, \ldots, c_{mi})$, where c_i's are the concept weights for product category *i*, in which $0 \le c_i$'s ≤ 1 and the product keyword vector of product *ij*, which belongs to product category *i*, is $\mathbf{WK}_{ij} = (k_{1ij}, k_{2ij}, \ldots, k_{nij})$, where k_{ij}'s are the keyword weights for product *ij*, in which $0 \le k_{ij}$'s ≤ 1. The user concept vector of some "anonymous" user at time *t* is $\mathbf{UC}_t = (c_{1t}, c_{2t}, \ldots, c_{mt})$, where c_t's are the concept weights for the user at time *t*, in which $0 \le c_t$'s ≤ 1 and the user keyword vector is $\mathbf{UK}_t = (k_{1t}, k_{2t}, \ldots, k_{nt})$, where k_t's are the keyword weights for the user at time *t*, in which $0 \le k_t$'s ≤ 1.

A two-phase four-step adaptive product recommendation process is developed.

Phase I: Searching for product categories of interest to users

Step 1: At time t, calculate the vector inner product of $\mathbf{UC}_t$ and $\mathbf{WC}_i$ for product category i.
$C_{ti} = \mathbf{UC}_t \cdot \mathbf{WC}_i = c_{1t}c_{1i}+c_{2t}c_{2i}+\ldots+c_{mt}c_{mi}$, $i = 1,\ldots, M$, where M is the number of product categories in the product data repository.

Step 2: For a product category i, if C_{ti} is greater than or equal to the predefined threshold θ then it is considered to be one of the product categories of interest to users (UserClassSet). Only those products belonging to the product categories included in UserClassSet are considered as candidates for products of interest to users.

Phase II: Searching for products of interest to users

Step 3: Calculate the vector inner product of $\mathbf{UK}_t$ and $\mathbf{WK}_{ij}$ for product ij, where ij belongs to product category i that is included in UserClassSet.
$K_{tij} = \mathbf{UK}_t \cdot \mathbf{WK}_{ij} = k_{1t}k_{1ij}+k_{2t}k_{2ij}+\ldots+k_{nt}k_{nij}$, $j = 1,\ldots, N_i$, where N_i is the number of products in product category i.

Only those keywords corresponding to *noteworthy concepts* are considered (see Figure 4). A concept vector attribute c_p is said to be a noteworthy concept of product category i if the weight c_{pi} in $\mathbf{WC}_i$ is greater than or equal to the predefined noteworthy threshold δ. The idea behind the noteworthy concept is that it is assumed if the weight of a concept is less than δ then the weights of its corresponding keywords might be so trivial that those keywords can be ignored to improve the system efficiency.

Step 4: The greater the value of K_{tij} is, the more appropriate to the user's interests the product ij is at time t. The system will then present products (across product categories) to the user in order based on the values of K_{tij}.

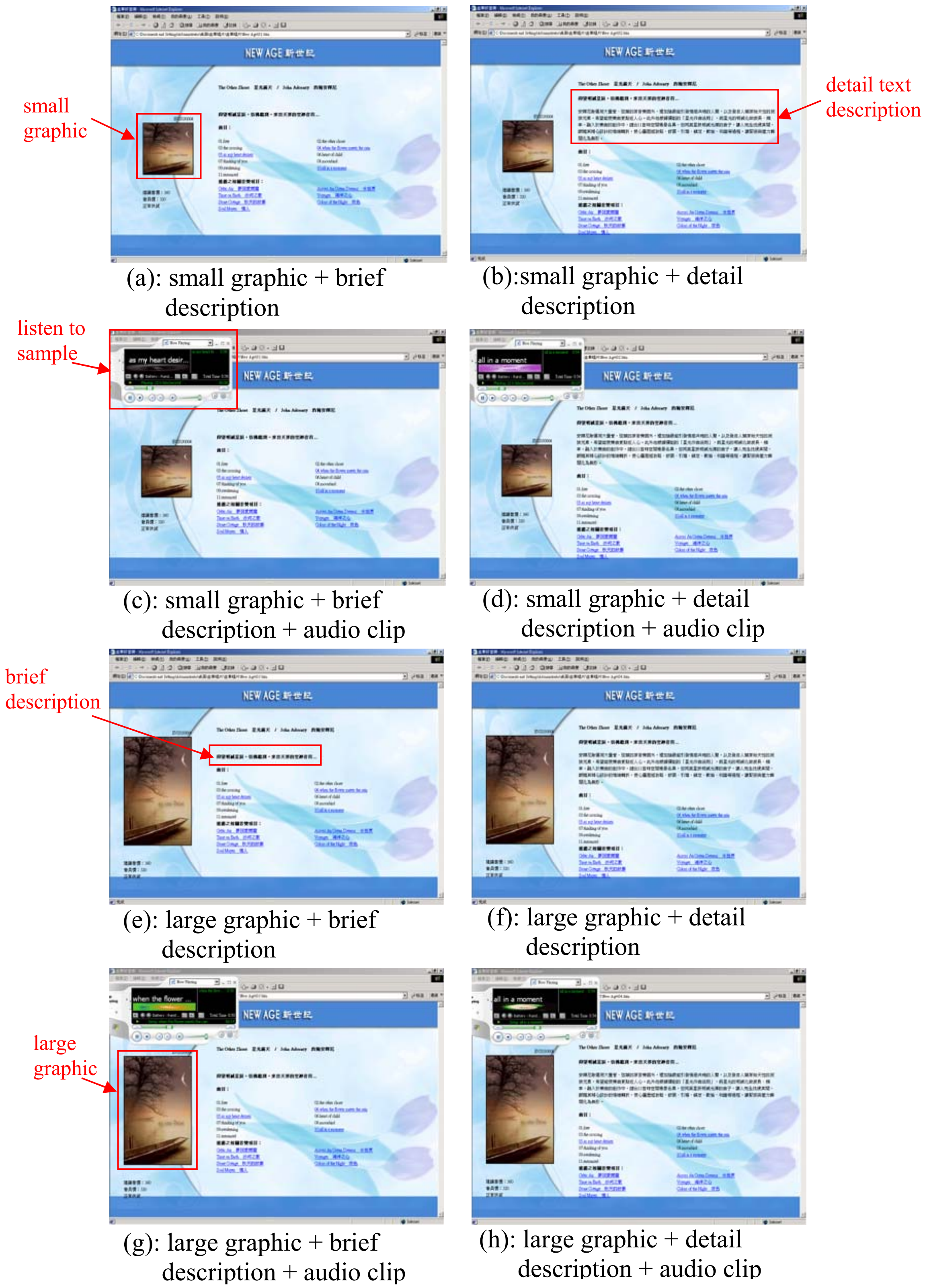
3.4 Adaptive Presentation of Product Data

To implement one-to-one marketing, this system provides not only the personalized product recommendation order (adaptive link support) but also the personalized presentation (adaptive presentation support) to the user. As the user becomes more interested in and selects a product item after viewing the presentation components, this system uses a frame variant based dynamic Web page to adaptively present the product data with respect to the user's media preference. Each product item is presented with several frames and each frame illustrates one media form, such as audio clips, graphics (large or small), and text description (detail or brief) (Figure 6).

The user media preference vector is represented as $\mathbf{UM}_t = (um_{1t}, um_{2t},\ldots, um_{qt})$, where um_{it} is the user media preference weight for a media combination i at time t, $-1 \le um_{it}$'s ≤ 1, in which q is the number of media combinations. The media preference vector is $\mathbf{WM}_t = (wm_{1t}, wm_{2t},\ldots, wm_{qt})$, where wm_{jt} is the media preference weight for a media combination j at time t. If a media combination j is selected at time t, then wm_{jt} is set to be 1. On the contrary, if a media combination *k* is stopped by the user while downloading at time *t*, then wm_{kt} is set to be -1.

In this research, the exponential smoothing procedure discussed in Section 3.2 is used to determine the user media preference.

$$\mathbf{UM}_{t+1} = \gamma \cdot \mathbf{WM}_t + (1-\gamma) \cdot \mathbf{UM}_t,\ \text{initially } (t=1),\ \mathbf{UM}_1 = \mathbf{WM}_1$$



(a): small graphic + brief description

(b):small graphic + detail description

(c): small graphic + brief description + audio clip

(d): small graphic + detail description + audio clip

(e): large graphic + brief description

(f): large graphic + detail description

(g): large graphic + brief description + audio clip

(h): large graphic + detail description + audio clip

Figure 6: Combinations of different media forms (Examples for Audio CDs)

As discussed in Zona Research (1999), 30% of the users will stop browsing if the Web page waiting time exceeds 8 seconds. To draw in customers, the usage of multimedia components, such as graphics and audio or video clips, is becoming more popular, however, if the bandwidth is not sufficient, Web page downloading time might become so long that the user may not wait. Therefore, after updating $\mathbf{UM}_{t+1}$, the system will present product data by considering the Web page downloading time.

A CGI (Common Gateway Interface) program is designed to detect the current transmission speed between the server and the client to estimate the possible Web page downloading time. Figure 7 demonstrates partial code of this CGI program. The possible Web page downloading time is estimated by dividing the Web page size with the current bandwidth. For $\mathbf{UM}_{t+1}$, let M_{t+1} = MAX{um_{t+1}'s}, then the adaptation process is as follows,

```
<!--
time = new Date();
endtime = time.getTime();
if (endtime == starttime)
      {downloadtime = 0
      }
else
      {downloadtime = (endtime - starttime)/1000;
      }
if (downloadtime == 0)
      {downloadtime = .1;
   nextpage = '<meta http-equiv="refresh" content="3; URL=System.cgi">'
            nextsize        = 50;
      }
else
      {nextpage        = '<meta http-equiv="refresh" content="3; URL=System.cgi">';
            nextsize        = 50;
      }
kbytes_of_data = 50;
linespeed = kbytes_of_data/downloadtime;
kbps = (Math.round((linespeed*8)*10*1.02))/10;
kbytes_sec = (Math.round((kbytes_of_data*10)/downloadtime))/10;
dltime_add10 = Math.round((kbytes_of_data*1.15)/kbytes_sec);
dltime_sub10 = Math.round((kbytes_of_data*0.85)/kbytes_sec);
// -->
```

Figure 7: The program to detect Web page downloading time (partial)

Step 1: If the estimated possible Web page downloading time for the media combination represented by M_{t+1} is smaller than or equal to 8 seconds, present product data with the media combination represented by M_{t+1}.

Step 2: If the estimated possible Web page downloading time for the media combination represented by M_{t+1} is greater than 8 seconds, find the next largest um_{t+1} and let it be the new M_{t+1}.
Back to Step 1.

The other media forms not included in M_{t+1} will be presented as hyperlinks. If the user still wants to select a medium not shown whose downloading time is greater than 8 seconds, the system will remind the user with the estimated possible downloading time and the preference weight for this media combination will be increased.

For example, if the sequence of media combination preference is (A, B, C, D, E) and the corresponding estimated downloading times are (A, 8.5 seconds), (B, 7.8 seconds), (C, 10.2 seconds), (D, 3.1 seconds), and (E, 6 seconds). Initially, the system evaluates media combination A. Since the estimated downloading time of A is greater than 8 seconds, the system, then, evaluates media combination B. Since the estimated downloading time of B is smaller than 8 seconds, hence, the system will present media combination B to the user and present A, C, D, and E as hyperlinks. However, if the user wants to select A or C, the system will warn the user with the estimated downloading time.

4. Experiments

4.1 Experimental Settings

The experimental system was based on a client/server structure and developed using Microsoft Windows 2000 in conjunction with IIS 5.0. The server was Intel P4 2.4G CPU with 512MB RAM. The user interface was developed with PHP. The database was developed with MySQL.

Since this research is to develop an adaptive Web-based product recommendation system with considering the user's interests, the user's media preferences and the Web page downloading time, it is essential to build an experimental system with products that can be easily presented with multiple media formats. To this end, the audio CD is a good candidate to serve as the product to be recommended for experimental purposes due to the following two reasons: (1) There are numerous audio CDs and they can be properly categorized due to the existence of significant differences. (2) Audio CDs themselves are multimedia products so that not only can the products be presented with texts, graphics, or audio clips but also the multimedia files can be used to evaluate the proposed adaptive presentation support, which is based on the Web page downloading time.

In this experiment, 1324 audio CDs, categorized into 9 categories, were included in the product data repository. The number of CDs in each product category ranged from 97 to 179. A product keyword vector included 229 keywords and a product category concept vector included 18 concepts. The product keyword vectors, the product category concept vectors, product keyword weights, and product category concept weights were defined intuitively.

Sixty two college students majoring in Information Management participated in the experiment. Among them, fifty one students used high bandwidth networks such as ADSL, Cable modem, and the Taiwan academic network (TANET). The other eleven students used the dial-up low bandwidth network.

This research used the technology acceptance model (TAM) to evaluate the proposed adaptive product recommendation system. TAM is generally considered the most robust, efficient, and influential in explaining adoption behavior of information technology and information systems (Davis, 1998). According to TAM, two determinants, usefulness and ease of use, serve as the basis for attitudes toward using a particular system, which in turn determines the intention to use, and then generates the actual usage behavior. Perceived usefulness refers to the extent to which a person believes that the information provided by a system would be useful. Perceived ease of use refers to the extent to which a person believes that using a system would be free of mental effort. Attitude to use is defined as the mediating affective response between usefulness and ease of use beliefs and intentions to use a target system. Intention to use is the subjective probability that users will use the system (Lu et al., 2003). Through its many years of use, TAM's power to predict use of information systems has received extensive empirical support through validations, applications, and replications (Lu et al., 2003).

The TAM model and hypotheses used in this experiment are illustrated in Figure 8.

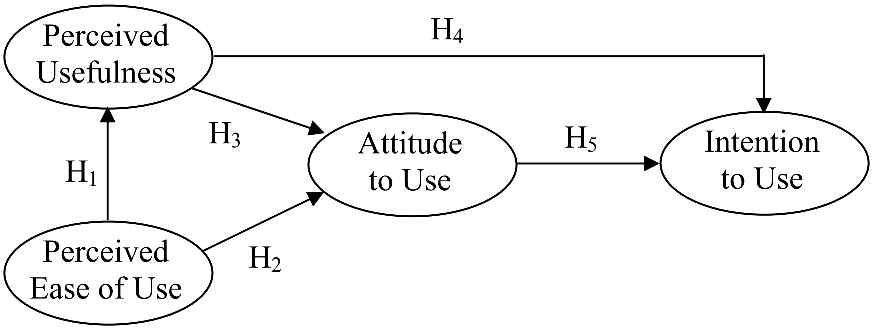


Figure 8: Technology acceptance model (TAM)

H_1: The perceived ease of use has significant positive effect on perceived usefulness.

H2: The perceived ease of use has significant positive effect on attitude to use.

H3: The perceived usefulness has significant positive effect on attitude to use.

H4: The perceived usefulness has significant positive effect on intention to use.

H5: The attitude to use has significant positive effect on intention to use.

In addition, to evaluate the effect of the proposed system for different bandwidth users, the following hypotheses are also tested:

H_6: There is no significant difference on perceived ease of use between high bandwidth and low bandwidth users.

H_7: There is no significant difference on perceived usefulness between high bandwidth and low bandwidth users.

H_8: There is no significant difference on attitude to use between high bandwidth and low bandwidth users.

H_9: There is no significant difference on intention to use between high bandwidth and low bandwidth users.

4.2 Results of the Experiment

To evaluate the above model, a 16-item questionnaire based on a 5-point Likert scale was used (Table I). In this questionnaire, items E1 and E2 were designed to evaluate perceived ease of use; items U1-U7 were designed to evaluate perceived usefulness; items A1-A3 were designed to evaluate attitude to use; and items I1-I4 were designed to evaluate intention to use.

The model was tested using SPSS 10.0. As shown in Table II, the construct reliability ranged from 0.7203 to 0.8729. Figure 9 presents the results of the structural model with significant paths as solid lines. The path coefficient from perceived ease of use to perceived usefulness was significant at $P < 0.001$ (β=0.532). Therefore, H_1 was supported. The effect of perceived ease of use on attitude to use the proposed system was also statistically significant with β=0.386 at P=0.002. The effect of perceived usefulness on attitude to use the proposed system was strong, as shown by the path coefficient of 0.781 ($P < 0.001$). Therefore, H_2 and H_3 were supported. The path coefficient (β=0.705) from perceived usefulness to intention to use the proposed system was also statistically significant at $P <$

0.001. The effect of attitude on intention to use the proposed system was quite strong, as shown by the path coefficient of 0.800 ($P < 0.001$). Therefore, H_4 and H_5 were supported.

Table 1: Experimental questionnaire
(5=strongly agree; 4=agree; 3=undecided; 2=disagree; 1=strongly disagree)

Item no.	Description	Mean	S.D.
E1	The functions provided by this Web site are easy to use.	3.87	.69
E2	The Web site is designed clearly and easily to understand.	3.74	.83
U1	This Web site is a good source for audio CDs.	3.66	.96
U2	This Web site can recommend the audio CDs fits your interests.	3.66	.92
U3	This Web site can help you quickly find the interested audio CDs.	3.71	.89
U4	The audio CDs this Web site recommended are related to the CD item you clicked.	3.92	.61
U5	The audio CDs this Web site recommended are related to the CD item you want to find.	3.71	.71
U6	This Web site can provide the graphics matching the bandwidth you used.	3.92	.58
U7	This Web site can provide the audio clips matching the bandwidth you used.	4.03	.54
A1	You would give high evaluation to this Web site.	3.60	.78
A2	You like to use this Web site.	3.73	.85
A3	It was a wise decision to use this Web site.	3.66	.79
I1	You will visit this Web site again.	3.69	.92
I2	Overall, you will be more willing to use the Web site than other sites.	3.26	.97
I3	If your needs are not clear, you will be more willing to use the Web site than other sites using indexing or searching mechanisms.	3.97	.65
I4	If your needs are clear, you will be more willing to use the Web site than other sites using indexing or searching mechanisms.	3.58	.86

Table II: Descriptive statistics of the questionnaire

Construct	No. of items	Mean	S.D.	Cronbach's α
Ease of use	2	3.8065	0.6736	0.7203
Usefulness	7	3.8387	0.5016	0.7982
Attitude to use	3	3.6613	0.7205	0.8729
Intention to use	4	3.6250	0.6817	0.8039

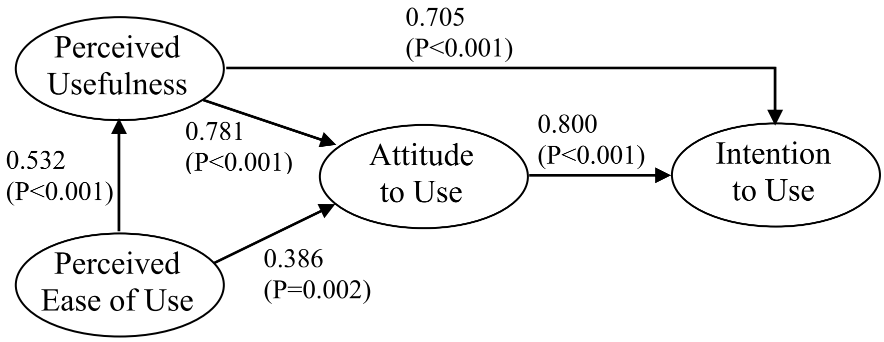


Figure 9: Results of TAM analysis

Table III shows the descriptive statistics of high bandwidth and low bandwidth users. As shown in Table IV, hypotheses H_6, H_7, and H_8 were supported, i.e., for perceived ease of use, perceived usefulness, and attitude to use, there were no significant differences between high bandwidth and low bandwidth users. However, H_9 was not supported, i.e., the low bandwidth users had higher intention to use the proposed system. This might be because the proposed system adaptively presented the media component to the user based on the Web page downloading time, which meant that the low bandwidth users did not wait as long they had expected, and hence increased the intention to use of the low bandwidth users.

Table III: Descriptive statistics of high bandwidth and low bandwidth users

Construct	Bandwidth	No.	Mean	S.D.
Ease of use	high	51	3.8824	0.6602
	low	11	3.4545	0.6502
Usefulness	high	51	3.8824	0.5233
	low	11	3.6364	0.3325
Attitude to use	high	51	3.6536	0.7423
	low	11	3.6970	0.6404
Intention to use	high	51	3.5588	0.7221
	low	11	3.9318	0.3180

Table IV: t-test between high bandwidth and low bandwidth users

Construct	Equality of variance	F test for variance		t test for mean		
		F	P	t	d.f.	P
Ease of use	equal	0.080	0.778	1.954	60	0.055
	unequal			1.974	14.796	0.067
Usefulness	equal	2.070	0.155	1.490	60	0.141
	unequal			1.981	22.271	0.060
Attitude to use	equal	0.701	0.406	-0.180	60	0.858
	unequal			-0.198	16.360	0.846
Intention to use	equal	7.183	0.009*	-1.670	60	0.100
	unequal			-2.677	35.764	0.011*

In addition, according to the experimental results, several findings were obtained. The subjects agreed that the experimental system could recommend audio CDs they were interested in (U1, U2, U4, and U5). Furthermore, the subjects were more willing to use the experimental system if their needs were not clear (I3). This implies that the proposed model can be especially beneficial for those users who do not know their real needs and/or do not know how to clearly specify their needs. The subjects also agreed that the experimental system could provide the graphics and audio clips matching the bandwidth they used (U6 and U7). For system efficiency, the subjects agreed that the experimental system could help them quickly find audio CDs of interest (U3). This can also be supported by the average browsing time recorded by the system (119 seconds) for the user to obtain a CD of interest.

5. Conclusions

An adaptive Web-based system is helpful for personalization, which is indispensable for modern electronic commerce. Adaptation decision in adaptive Web-based systems is based on the user's characteristics represented in the user model. Estimating the user's characteristics, hence, is the key to developing adaptive Web-based systems. However, while estimating the user's characteristics, most systems may face problems such as (1) users are not motivated to answer questions; (2) users may not clearly know their own needs or how to specify the keywords for searching; (3) users' interests may change over time; (4) learning the user's interests by data mining might be inapplicable for those sites without enough user data; (5) keeping, monitoring, and recording users' browsing behavior may invade user privacy; and (6) most sites implement personalized services for "previous" customers only. Moreover, though purchasing decision is highly dependent on the user's media preferences, few adaptive Web sites provide product recommendation based on the user's media preferences. In addition, the Web page downloading time may be so long that it decreases the user's interest in browsing. To this end, this research develops an adaptive product recommendation system for anonymous new customers based on their interests, media preferences, and the Web page downloading time.

In order to protect the user's privacy, a temporary user model is constructed when the user enters the system and deleted when the user leaves the system. The user remains anonymous throughout the browsing session. Through observing the user's browsing behavior, the system can estimate the user's current interests by incremental learning. Estimating the user's interests without asking the user to answer any questions and/or fill out forms will neither interrupt the browsing processes nor decrease the user's will to browse. This research also considers the effect of changing user interests over time. By using the exponential smoothing procedure, the user's interests are estimated smoothly by increasing the weight of more recently selected information so that the system can track incremental changes of user interests. For the issue of system performance, a two-layer product catalog structure and a two-stage breadth-first search algorithm are proposed to reduce system load so that the possibility of real-time recommendation is increased. As the user becomes interested in and selects a product, this system uses a frame variant based dynamic Web page to adaptively present product data appropriate to the user's media preference and the Web page downloading time.

A TAM model was used to evaluate the proposed adaptive product recommendation system. The experimental results revealed the perceived ease of use and perceived usefulness of the proposed system can have significant positive effects on the user's attitude and intention to use the proposed system. For perceived ease of use, perceived usefulness, and attitude to use, there were no significant differences between high bandwidth and low bandwidth users. However, the low bandwidth users had higher intention to use the proposed system. In addition, the experimental results revealed that the subjects agreed that the experimental system could recommend the audio CDs they were interested in and that they were willing to use the experimental system, especially, when their needs were not clear. This implies that the proposed model can be especially beneficial for those users who do not know their real needs and/or do not know how to clearly specify their needs. The subjects also agreed that the experimental system could provide the graphics and audio clips matching the bandwidth they used. For system efficiency, the subjects agreed that the experimental system could help them quickly find audio CDs of interest to them.

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