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Exploring Learner Attitudes toward Web-based Recommendation Learning Service System for Interdisciplinary Applications

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ABSTRACT

The booming digital-content industry has resulted in an increasing number of e-learning Internet websites that provide online learning services. Recommendations for learning sites are used by diverse learners to identify the most appropriate learning resources. However, research into recommendations about learning has concentrated primarily on suggestions for teaching materials to be used in a particular learning program, and studies have focused on improving the techniques underlying these recommendations without addressing the possibilities for interdisciplinary learning or changes in learner preferences. This study implemented and evaluated a system that recommends interdisciplinary pedagogical resources while recognizing changes in the foci of educational efforts and interests. This system was designed to satisfy individualized learning demands by recommending the most suitable content within an interactive context. Evaluations of learners' attitudes and intentions after using the proposed system revealed widespread acceptance. Data analysis demonstrated that system stability and interface satisfaction were the key factors in learners' attitudes. Indeed, interface satisfaction was the strongest predictor of recommendation accuracy and content satisfaction.

Keywords

Recommendation learning, Interdisciplinary application, Leaner attitudes

Introduction

The huge quantity of learning resources currently available online has led to information overload, and traditional search engines can no longer meet the needs of all e-learners (Howe & Dreilinger, 1997; Pinkerton, 2000; Yan & Garcia-Molina, 1995; Zamboni, 1998) because these tools often provide irrelevant information while ignoring related content (Goldberg, Nichols, Oki, & Terry, 1992). These so-called recommendation systems aim to identify the appropriate learning materials among the e-learning resources available to help learners make appropriate choices (Resnick & Varian, 1997). Although only high-quality materials are presumably recommended to learners, such materials may not meet learners' expectations. For this reason, most current studies have focused on identifying information that meets the particular needs of learners (Wei, Moreau, & Jennings, 2005).

Current educational recommendation services use either explicit or implicit ratings. Calculations of explicit ratings are based on learners' input on such issues as interest in courses, quality of learning units, and difficulty of teaching materials. Thus, although the accuracy of these recommendations is high, excess data may present a burden to learners. Lang (1995) proposed a recommendation service that rated articles via browsers that would analyze and reorganize the ratings of previous readers to offer further recommendations to learners who have not yet read the articles (Krulwich & Burkey, 1997). Unlike explicit ratings, which are based on learners' expressed learning preferences, implicit ratings automatically record learning paths (e.g., learning materials read by learners, time spent on each learning unit, and frequency of daily visits to the learning website) for analysis. However, greater numbers of paths would require longer amounts of time for the calculation of recommendation rules; such implicit ratings are usually used to develop personalized recommendations for websites. A typical example of an implicit rating system was presented by Rucker and Polanco (1997), who suggested that the addition of a website to a list of bookmarks indicates interest in that website. Therefore, similar preferences can be calculated on the basis of the bookmarked sites and used to recommend additional websites.

Previous research on the recommendation of learning services has usually focused on recommendations for one course, with the goal of continuously creating different recommendation algorithms to enable learners to obtain more precise content (Johannes, Matthias, Christoph, & Ralf, 2008; Tasi, Chiu, Lee, & Wang, 2006; Wei et al., 2005). However, these studies have neglected immediate individual interactive learning models based on interdisciplinary learning, new fields of learning, and changes in academic interests. Content restricted to single subject cannot meet the diverse needs of modern industrial development, and interdisciplinary learning and cooperation have emerged as approaches for learners trying to solve complicated professional issues. From a psychological perspective, interaction between different fields and domains of knowledge can trigger learners' intellectual potential, and exposure to multiple domains can enhance the scope, depth, and novelty of knowledge (Johansson, 2006). Thus, this study examined a platform for a recommendation service that supports interdisciplinary learning and used the advantages of explicit and implicit ratings to develop a mechanism for detecting changes in academic interests. Such a mechanism enabled the system to recognize each learner's learning process and to actively recommend content from the specific fields required by learners. It also provided precise recommendations for learning content and reused pedagogical resources.

This study was designed to implement an interdisciplinary recommendation system that provides educational suggestions while monitoring changing academic interests to meet the individualized interactive learning demands of learners by recommending content that is appropriate to their current needs. We also evaluated learners' attitudes and intentions with respect to using an interdisciplinary recommendation service. The study examined the predictive relationships among five factors: system stability, interface satisfaction, recommendation accuracy, satisfaction with content, and system acceptance. In this way, the functions of our system could be expanded and altered on the basis of the needs and attitudes of learners.

Literature Review

Social–cognitive theory (SCT) describes an individual's behavior in terms of a reciprocal feedback system involving environment, personal attributes, and behaviors (Bandura, 1977). SCT has been applied in studies of education, decision making, management, and computer skills (Compeau & Higgins, 1995; Wood & Bandura, 1989; Zimmerman, 1990). The theory of reasoned action (TRA), as proposed by Fishbein and Ajzen (1975), can integrate previous theories on the influence of attitudes on behavior. This theory assumes that behavior can be controlled by an individual's will, which could thus be used to predict and explain individual behaviors. However, the theory is usually restricted by many factors that significantly reduce its explanatory power regarding individual behavior. To enhance the predictive power of the TRA, Ajzen (1985) added factors related to perceived behavioral control over two dimensions that presumably influence behavioral intentions, namely attitudes toward behavior and subjective norms, to form the theory of planned behavior (TPB). The technology acceptance model (TAM), developed by Davis (1989) based on the TRA, provides general explanations about an individual's actual and predicted use of information technology. The TAM has served as a theoretical foundation for investigations into the influences of external variables and users' attitudes on use intentions. These studies have suggested that perceived usefulness and ease of use influence attitudes regarding the use of technology and further affect behavior. Previous empirical studies have found that users' attitudes directly influenced use intentions. At present, the TAM is widely applied in various fields such as information systems (Heijden, 2003), e-learning systems (Ndubisi, 2006), online shopping, and online gaming (Gefen, Karahanna, & Straub, 2003; Hsu & Lu, 2004).

Most research papers have focused on improving the techniques used in web-based recommendation learning systems (Chen, 2005; Cunningham & Frank, 1999; Krulwich & Burkey, 1997; Wang, Chuang, Hsu, & Keh, 2004). Nevertheless, understanding learners' attitudes can also help to expand system functions and meet learners' needs, which should further increase the impact of learning and enhance satisfaction with the learning process. The present study differs from previous studies in providing only a description of technology-oriented deduction (Chen, 2005; Cunningham & Frank, 1999; Krulwich & Burkey, 1997; Wang, Chuang, Hsu, & Keh, 2004). We used a questionnaire format to understand the reactions of learners to using a web-based learning system for recommending interdisciplinary learning resources. The attitudes of learners are crucial to the successful development of such a web-based recommendation learning system. For this reason, we adopted the Three-tier Use Model (3-TUM) proposed by Liaw (2007), which emphasizes individual attitudes toward information technology and has been widely employed in many important studies of user attitudes (Liaw & Huang, 2003; Liaw, Huang, & Chen, 2007; Lai, Huang, Liaw, & Huang, 2009). Perhaps most importantly, we integrated SCT, TPB, and TAM while simultaneously considering individual experiences, system quality, affective and cognitive factors, and behavioral intentions (Triandis, 1971; Davis, Bagozzi, & Warsaw, 1989; Moon & Kim, 2001; Liaw & Huang, 2003). We used a validated survey to quantitatively examine the influences of individual experiences and system quality on the affective and cognitive reactions of users; we were then able to ascertain how users' reactions then affected behavioral intentions.

Previous studies have explored the factors that influence the use and acceptance of e-learning systems. Ozok, Fan, and Norcio (2010) reported a significant positive correlation between a system's predictive consistency and the accuracy of its recommendations and noted that learners considered system reliability to be an important factor in their use of a system. Interface satisfaction refers to the convenience experienced by learners when using a system insofar as it conforms to the operational habits of learners (Nielsen, 1993; Rushieks & Rushineks, 1986). Chien (2009) noted a significant positive correlation between interface satisfaction and content satisfaction. E-learning systems must offer stability and user-friendly interface to continue to attract learners, motivate them to visit learning websites, and explore the relationships among predictive factors and systems-management issues in the affective and cognitive reactions of learners (Shneiderman, 1997). Literature using specific reading or instructional materials as indicators of use intentions (Chen & Yeh, 2008; Hu & Pu, 2009; and Kuan, 2004) has found a significant positive correlation between recommendation accuracy and intent to use e-learning resources. Recommendation accuracy refers to whether the suggested content satisfies learners' demands and influences their future use intentions. A study conducted by Chang (2010) on the use and acceptance of mobile learning communities found that satisfaction with the educational content affected acceptance of the system.

Thus, the accuracy of the recommendations and the satisfaction with the content offered by e-learning systems can be investigated as measurable variables (Chang, 2010). Indeed, Baker-Eveleth, Eveleth, O'Neill, and Stone (2006) examined laptop exams; Cheng-Chang, Gunter, Sivo, and Cornell (2004–2005) explored e-learning management systems; and Ndubisi (2006) analyzed the online learning community's acceptance of a particular system. According to research performed by Simonson, Smaldino, Albright, and Zvacek (2000), the following four important factors enhanced learners' use of information technology: learners' attitudes, experiences, cognitions, and learning styles. Of these factors, learners' attitudes were found to be the most important indicator of satisfaction. After gaining learners' acceptance, a learning system should meet learners' demands by increasing its functions to enhance learning.

Hypothesis 1: Five factors affect use intention with web-based systems designed to recommend interdisciplinary educational resources to learners: system stability, interface satisfaction, recommendation accuracy, content satisfaction, and system acceptance.

The 3-TUM research framework proposed by Liaw (2007) is currently widely used in many important studies on learners' attitudes (Lai et al., 2009; Liaw & Huang, 2003; Liaw et al., 2007). The major conceptual foundation of this approach draws on SCT, TPB, and TAM to explore the attitudes of the users of information technology at three different levels: individual experiences and system quality, affective and cognitive reactions, and behaviors and intentions. The level of individual experiences and system quality identifies the events that can influence affective and cognitive reactions. Quantification at the affective and cognitive level allows for predictions about intentions and behaviors (David et al., 1989; Liaw, Chen, & Huang, 2008; Triandis, 1971). In other words, individual experiences and system quality can positively influence affective and cognitive experiences. At the same time, affective and cognitive dimension can also positively impact behaviors and intentions. Extant literature shows that system stability and interface satisfaction were included in the category of system quality, whereas recommendation accuracy and satisfaction with content constituted cognitive factors, and behaviors and intentions were related to system acceptance.

Hypothesis 2a: System stability and interface satisfaction can positively predict recommendation accuracy and content satisfaction.
Hypothesis 2b: Recommendation accuracy and content satisfaction can positively predict system acceptance.

Development of a web-based learning system for recommending interdisciplinary learning resources

During the process of e-learning, learning guides help each learner navigate through materials according to their abilities, interests, habits, and needs. Traditional classroom teaching uses the same schedule for all learners under the assumption that all have similar capabilities. Learners using recommendation services are regarded as unique individuals with particular learning abilities and preferences. They are allowed to use materials at their own pace and are expected to have personalized learning experiences. Moreover, the system records every completed learning process to enable understanding of the learning schedule and status of each learner as well as to provide learners with clear insight into their own status as learners.

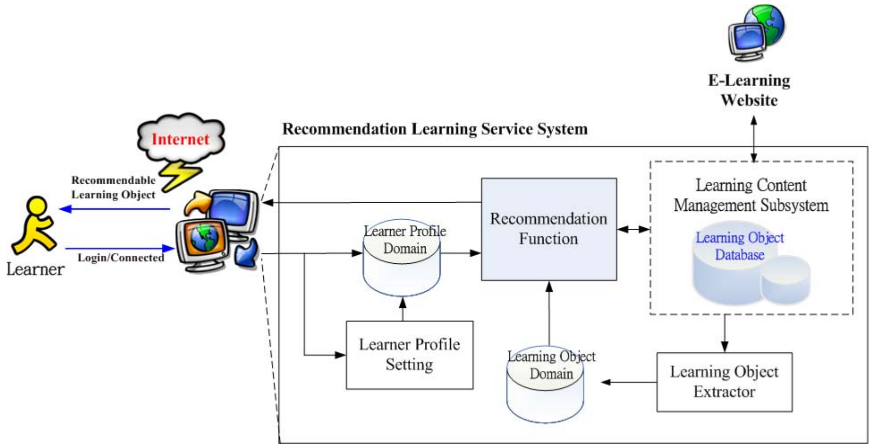

Figure 1. The framework of interdisciplinary recommendation learning service system

The proposed recommendation service is presented in Figure 1. Learning objects are transformed into vector-based representations through a learning-object extractor and are then stored in the learning-object domain. The learning-content-management subsystem (LCMS) stores the learning objects in the database in the form of a shared content-object reference model (SCORM). Learning objects can be in the form of text, graphics, videos, and simulation clips, which enable their repeated use as the system expands to include additional learners. Initially, new learners will be guided to a survey to examine their interests, and these data will be used to establish individualized learning profiles. Previous users will be sent directly to the learner-profile domain to obtain their personal profiles. Next, the system's recommendation operations will identify the appropriate learning objects. Learning objects with the highest scores will be recommended to learners, as shown in Figure 2.

The following four courses will be saved in the database of the system: basic computer concepts (BCC), databases, networks, and web design. This study classified these courses according to the characteristics of their teaching materials. The difficulty of materials was divided into low, medium, and high. The time required to learn the materials was classified as within 30 minutes, 30–60 minutes, and more than 60 minutes. The types of teaching materials included introductory, theoretical, practical, and mathematical. Introductory material presents foundational concepts, theoretical material teaches logic or epistemology, practical material involves the use of software, and mathematical material involves methods of calculation. The extended object-oriented portal system (XOOPS) was selected as the infrastructure for this web-based service.

Figure 2. Screensnap of an interdisciplinary web-based recommendation learning service system

The recommendation function is key success factor to recommend learning service system which mainly introduces the advantages of explicit and implicit ratings to proceed a design. A cross validation is conducted on the data generated from explicit and implicit ratings, and add on the hottest recommended principle Top-N into the attribute value of learning interest table and proceed sieving (Karypis, 2001; Sarwar, Karypis, konstan, & Riedl, 2000), to sieve out the course materials that interests no learners, and to use association rules at the same time to analyze the e-portfolio of each learner to achieve the learning contents required by the learner to enhance the accuracy of recommended course materials (Agrawal & Srikant, 1994; Chen & Liu, 2004). In consideration of interdisciplinary learning of learners, we design an effective multidimensional system to detect the change in learning; including three following operating rules: (1) if learners choose learning contents of different subjects from learning interest table, and when the number of clicks exceeds minimum support count, the system will take the new-added field and will recommend the learning materials of this new-added subject automatically. (2) if learners did not click on the learning contents recommended by the system when the number of clicks exceeds minimum support count, the system will acknowledge a change of learning interest and remove the recommended course material of this subject. (3) if the system reports a failure on recommendation, in other words, did not conform to the learning contents that learners want, then a weighed adjustment strategy on explicit and implicit ratings will be enabled to increase the weighted of e-portfolio analytic results and to proceed a recommendation to learning contents again.

For example, learners only click on the e-learning courses while setting their learning interest, after a period of time, perhaps, they will see a need in interdisciplinary learning, as implementation of e-learning website would require homepage design knowledge, the system will automatically detect number of clicks on learning contents of webpage design. In order to avoid error detection of learners caused by random browsing, number of clicks has to exceed minimum support count defined by the association rule (Agrawal, Imieliński, & Swami, 1993) to allow the system to acknowledge the new-added field that learners belong to, and automatically recommends the learning contents of webpage design course to learners.

After the system recognizes these correct clicks, new lists are expanded and new recommendation contents can be formed. The recommendation function is shown as Figure 3 and the following are recommendation measures by an example:

- Step 1: selection of interested learning items in the system and setup of learning profile.
- Step 2: records of interested learning items. Filtering learning contents in accordance with the learning profile orderly based on interested subject, level of learning content, learning time and learning style.
- Step 3: analysis and cross validation over the path linked list formed through the association rules, in order to find out a learning content with functions over minimum support count.
- Step 4: detection of changing learning process to adjust setting of learning fields.
- Step 5: a customized recommended learning list is produced by calculation of recommendation functions based on the weighted ratios. Namely, the system demonstrates the recommended learning contents based on the ratio of implicit and explicating rating setting by the system administrator.
- Step 6: readjust the recommended learning lists once the recommendation fails by starting weighted adjusting strategy.

Figure 3 presents the illustration operations of a recommendation function. In the first step, learners set a learning profile and subject of BCC. Learning difficulty is the primary level, the learning time is 30-60 minutes, and learning type is practice. In this step, learners access setting in registration of the recommendation learning system. The system will automatically record each learner in a database. In the second step, the system will show a screen database of learning materials according to each learner's learning profile. These two steps are explicit rating. The third step is implicit rating. The system will record each learner's teaching materials as a learning path and select teaching materials upon association rules. For instance, the P_1 learning path is shown by $\{B_1, B_2, B_3\}$, and it means the order of learners' reading materials is B_1, B_2, and B_3. Therefore, learning paths P_1, P_2, and P_4 would be selected with the minimum support count assumed as 3. In the fourth step, the system will calculate the mixture of explicit rating and implicit rating, and include the teaching materials recommended learning list. After detection of a changing learning process, the mechanism demonstrates that although the web design course is not the subject listed as interesting learners in learning profile, the learners usually read the teaching materials for web design course, which is not random reading. The system will recommend teaching materials regarding the web design course, as it is a mechanism of interdisciplinary recommendation learning. In the fifth step, a recommended learning material list will be shown to registered learners. However, if learners do not read the recommendation teaching materials, the recommendation will fail. The system will continue with the next recommendation by weighted adjusted strategy to offer more accurate recommended teaching materials.

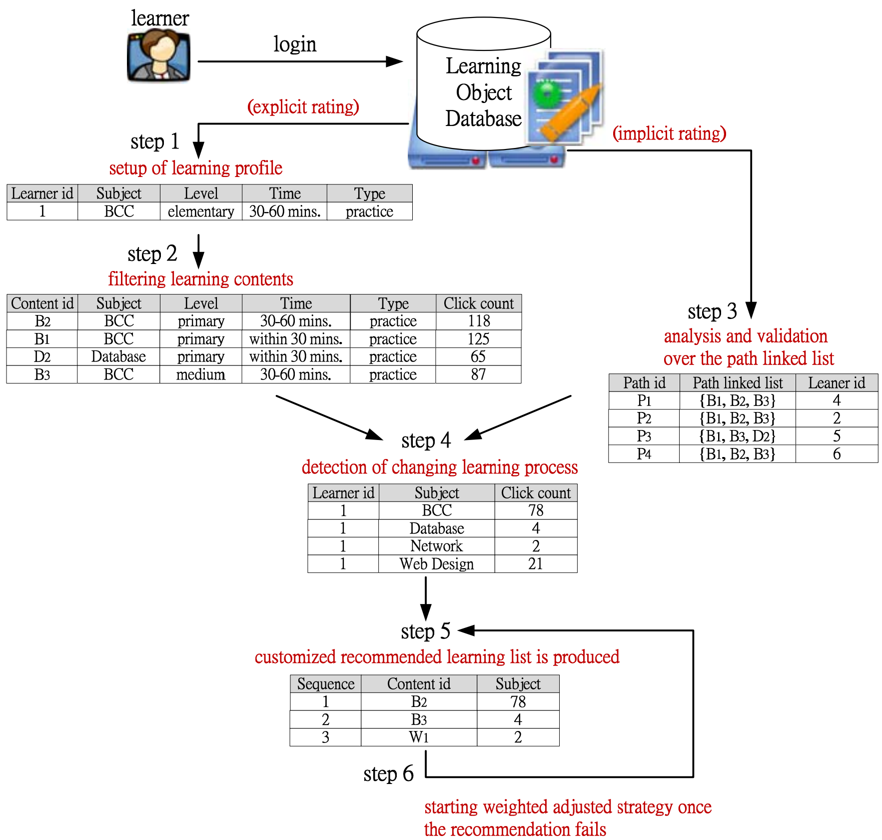

Figure 3. Recommendation function for interdisciplinary learning

Research Design

Our sample consisted of 195 students in IT-related departments at universities located in central Taiwan. A questionnaire was distributed to these students 6 weeks after they had used the web-based interdisciplinary recommendation system. Participants were engaged in using this system for an average of 72 hours prior to completing the survey. We received 182 valid questionnaires, which represented a response rate of 93.33%. The purpose of this experiment was to investigate learners' attitudes about the use of an interdisciplinary recommendation system. The items contained in the scale measuring these attitudes were adapted from the extant literature on web-based learning. Well-known experts were invited to discuss the validity of the questionnaire based on the relationship between our research purpose and the content and phrasing of the items in the scale. Questions with poor discriminative validity were eliminated, and ambiguous phrases were modified. A total of 22 questions using a 7-point Likert scale from 1 to 7 (representing strongly disagree to strongly agree) were included in the final instrument.

This study based on theories presented in previous studies (Chen, 2007; Liaw et al., 2008; Moon & Kim, 2001; Vankatesh, 1999), used a questionnaire methodology to understand the reactions of learners to a web-based system for recommending educational resources because learners' attitudes are crucial to the success of any web-based recommendation system. On the basis of our literature review, this study focused on system stability, interface satisfaction, recommendation accuracy, satisfaction with content, and system acceptance as key contributors to the attitudes of learners toward such a system.

Data Analysis and Results

Prior to performing factor analysis, we used the Kaiser–Meyer–Olkin (KMO) test and Bartlett's test of sphericity to examine the correlations among variables to determine their suitability for factor analysis. The test results revealed a

KMO value of 0.83, suggesting close correlations among variables. The *chi*-square value for Barlett's test of sphericity was 2798.70, which was significant and indicative of common factors that rendered the data appropriate for follow-up factor analysis. The study used principle-component analysis (PCA) for conducting the factor analysis in two steps. The first step, factor extraction, was used to calculate the variance shared among all variables. Eigenvalues higher than 1 were identified following Kaiser's rule, which defines the factors that can be used to explain variance in the results (Kaiser, 1958). We also used a scree test to identify the factors selected during extraction (Cattell, 1966). The second step, factor rotation, was performed to enhance our ability to explain factor loading. Factors with eigenvalues higher than 1 were selected for factor rotation. Varimax orthogonal rotation was used in this analysis because the simple structure of this approach easily explained the results.

Table 1 shows the five factors extracted in the factor analysis using the minimum factor-loading standard of 0.6 suggested by Hair, Black, Babin, Anderson, and Tatham (2009). The eigenvalues and percentages of variance obtained using Varimax rotation are also presented. Five items were contained in factor 1, five in factor 2, four in factor 3, four in factor 4, and four in factor 5. The five factors were system stability, interface satisfaction, recommendation accuracy, system acceptance, and content satisfaction. Table 2 shows the items included in the factors, the factor loadings, and their levels of reliability.

Table 1. Total variance explained and percentage of variance by Varimax method

Component	Eigenvalue	Percentage of variance	Cumulative percentage
1	3.68	16.73	16.73
2	3.39	15.43	32.16
3	3.14	14.25	46.41
4	2.97	13.51	59.92
5	2.78	12.64	72.56

We calculated Pearson's correlation coefficients to further assess the predictive power of the variables included in this study (Stevens, 1992). Path analysis, a statistical method for elucidating relationships among multiple variables, uses regression analysis to understand the relative influences of variables. However, problems of multicollinearity must be eliminated. Following the suggestions offered by Blumberg, Cooper, and Schindler (2008) and Neter, Wasserman, and Kutner (1990), we ensured that (1) the correlation between variables was less than 0.8 and (2) the variance inflation factors (VIFs) were lower than 10. Table 3 shows the Pearson's correlation coefficients between variables; significant correlations are those with coefficients less than 0.8. The results of stepwise multiple regression analyses are shown in Table 4, which also shows that the VIFs were lower than 10. The results of our research model are also shown in Figure 4. The first regression analysis examined the effect of system stability and interface satisfaction on recommendation accuracy. The results suggest that these two factors were independent predictors of recommendation accuracy ($F(2, 179) = 37.24$, $p = 0.000 < 0.001$, $R^2 = 0.30$). The second regression analysis examined the predictive power of satisfaction with content on system stability and interface satisfaction. Simply stated, the results indicated that system stability and interface satisfaction predicted content satisfaction ($F(2, 179) = 43.23$, $p = 0.000 < 0.001$, $R^2 = 0.33$). The final regression analysis examined the predictive power of recommendation accuracy and content satisfaction on system acceptance. The results showed that recommendation accuracy was more strongly predictive of system acceptance than was satisfaction with content ($F(2, 179) = 34.11$, $p = 0.000 < 0.001$, $R^2 = 0.28$).

Table 2. Reliability and factor analysis

No.	Items	Factor loading	Cronbach's α
Factor 1: System stability			
1.	The speed of system connection is good and no need to waste much time in waiting.	0.871	0.88
2.	The browse of teaching materials won't cause computers to crash.	0.771	
3.	I satisfied with the system connection speed.	0.805	
4.	There is no response delay on the system.	0.755	
5.	As a whole, I am satisfied with the system stability	0.726	
Factor 2: Interface satisfaction			
6.	System menu and links are clearly marked, which makes it easy and comfortable for me to browse.	0.740	0.87
7.	I feel the layout and the color arrangement of the system interface are	0.856	

	friendly.		
8.	I feel the layout and the color arrangement of the system interface make it easy to use.	0.777	
9.	I feel the steps of system setting are easy and convenient.	0.754	
10.	Overall, I am satisfied with the system's operating interface.	0.662	
Factor 3: Recommendation accuracy			
11.	When my learning preferences change, I find the teaching materials recommended by the system suit my needs.	0.833	0.88
12.	In the interdisciplinary learning, I find the teaching materials recommended by the system suit my needs.	0.770	
13.	The teaching materials recommended by system's recommendation function suit my needs.	0.772	
14.	All in all, I am satisfied with the recommendation accuracy of the system.	0.765	
Factor 4: System acceptance			
19.	I believe the system is helpful to my learning.	0.843	0.83
20.	I will use the system to assist my learning.	0.730	
21.	I will use the system to learn in the future.	0.618	
22	I think it is necessary to use the system in learning.	0.707	
Factor 5: Content satisfaction			
15.	The contents of the teaching materials recommended by the system suit my learning preferences.	0.736	0.84
16.	In terms of learning time, I am satisfied with the teaching materials recommended by the system.	0.734	
17.	In terms of learning styles, I am satisfied with the teaching materials recommended by the system.	0.796	
18.	As a whole, I am satisfied with the teaching materials recommended by the system.	0.711	

The results of the data analysis showed that system stability and interface satisfaction were the most important contributors to the attitudes of learners. System stability and interface satisfaction predicted recommendation accuracy and content satisfaction, respectively. Recommendation accuracy and content satisfaction also predicted system acceptance. These results are consistent with those reported by Ozok et al. (2010), Chien (2009), Hu and Pu (2009), and Chang (2010). Interface satisfaction was found to be the best predictor of recommendation accuracy and content satisfaction. After learners accept recommendation systems for educational resources, the accuracy of recommendations has the strongest predictive power with respect to learner reactions.

Table 3. Correlation analysis

variables	System stability	Interface satisfaction	Recommendation accuracy	System acceptance	Content satisfaction
System stability	1	0.467**	0.500**	0.509**	0.471**
Interface satisfaction		1	0.589**	0.500**	0.589**
Recommendation accuracy			1	0.585**	0.552**
System acceptance				1	0.480**
Content satisfaction					1

** $p<0.01$

Table 4. Regression results of predicted path relationships

Hypothesis	Dependent variable	Independent variables	β	R^2 change	p
H2a	Recommendation accuracy	System stability	0.36	0.18	0.000
		Interface satisfaction	0.35	0.12	0.000
H2a	Content satisfaction	Interface satisfaction	0.52	0.30	0.000
		System stability	0.17	0.03	0.008
H2b	System acceptance	Recommendation accuracy	0.42	0.25	0.000
		Content satisfaction	0.18	0.03	0.015

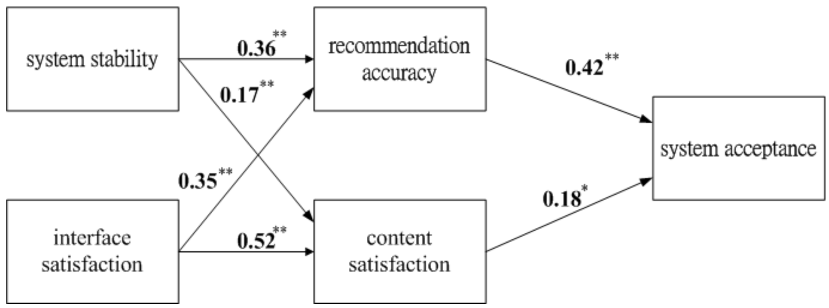

Figure 4. The results of research model.
*p<0.05, ** p<0.01

Discussion

The results obtained from the data analysis presented in Tables 1 and 2 are consistent with previous results related to learning attitudes (Liaw & Huang, 2003; Liaw et al., 2008), and they also support Hypothesis 1 of this research. In terms of the services provided by web-based recommendation services, learner attitudes can be divided into five factors: system stability, interface satisfaction, recommendation accuracy, satisfaction with content, and system acceptance. The factor loading for each factor was greater than 0.6, with Cronbach's α exceeding 0.8, which demonstrated the distinguishability and reliability of the factors and is consistent with the proposals of Hair et al. (2009). Two major factors should be considered in the development of a web-based recommendation environment: system stability and interface satisfaction. Delone and McLean (1992) advocated system stability as the key factor in ensuring the quality of an information system, whereas Liaw et al. (2008) found that learners were more concerned about user interface. On the other hand, the present study found that positive evaluations of usefulness and positive behavioral intentions were related to the accuracy of recommendations and satisfaction with content.

The statistical results of the regression analysis presented in Table 4 quantify learner attitudes toward services provided by the web-based recommendation learning system, validate Hypotheses 2a and 2b of this research, and support the 3-TUM model. When system stability and interface satisfaction were used to predict recommendation accuracy, system stability explained 18% of the variance in recommendation accuracy; when system stability and interface satisfaction were used to predict content satisfaction, interface satisfaction explained 30% of the variance in content satisfaction; and when recommendation accuracy and content satisfaction were used to predict system acceptance, recommendation accuracy explained 25% of the variance in system acceptance. Thus, interface satisfaction was the strongest predictor of recommendation accuracy and content satisfaction, whereas acceptance of a system offering web-based recommendations for learning resources was the most significant predictor of recommendation accuracy.

Conclusion

The ongoing development of network technologies has resulted in the availability of digitized knowledge on many digital-learning websites. Learners often get lost when faced with huge quantities of online learning resources, and consequently, many learning services focus on providing recommendations for course materials based on learners' interests. Learners no longer accept the need to engage in effortful searches for suitable digital teaching materials or for knowledge in other fields. Most previous studies related to recommendations for learning have focused on the accuracy of the digital teaching materials recommended for a single subject area but have neglected interdisciplinary learning, novel learning areas, and multidimensional recommendations. Our concept of a service offering interdisciplinary recommendations of learning resources would draw on massive online resources to identify precise interdisciplinary digital learning content for learners. This paper differs from past discussions of the technology-oriented basis of online environments designed to offer recommendations related to learning. Previous studies have focused on improving the performance of recommendation algorithms, whereas the present study focused on understanding the attitudes of learners and expanding the system functions to enhance learning effectiveness and satisfaction. Learner attitudes were surveyed after participants used the interdisciplinary recommendation learning system, and five factors were extracted: system stability, interface satisfaction, recommendation accuracy, content satisfaction, and system acceptance.

Working from an academic perspective, we proposed and implemented a service able to use innovative strategies to offer interdisciplinary recommendations and to automatically detect areas in which the interests and/or needs of learners have changed. This system can recommend suitable learning materials in the service of individualized learning. This study is also the first to use factor analysis in its examination of recommendation services for learning resources and to explore the attitudes and system acceptance of learners. Thus, our results support the 3-TUM model and the research hypotheses and serve as a foundation for the development of systems that recommend learning options. Working from a practical perspective, this study proposed four important elements of the proposed system: system stability, interface satisfaction, recommendation accuracy, and content satisfaction. Learners were most concerned with interface design and the accuracy of the recommendations for instructional material. Our data emphasized the importance of designing recommendation systems that allow learners to simply and conveniently use the services and that provide learning materials that conform to the learners' needs and interests. This study offers important contributions to the relevant literature by presenting innovative concepts regarding web-based interdisciplinary recommendations and by emphasizing the need for a system that is consistent with contemporary pedagogical conditions in its ability to enhance and effectively respond to diversity in learning.

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