Interactive Learning Environments
Vol. 17, No. 2, June 2009, 151–163

Investigation of users' preferences in interactive multimedia learning systems: a data mining approach

Kyriacos Chrysostomou, Sherry Y. Chen* and Xiaohui Liu

School of Information Systems, Computing and Mathematics, Brunel University, UK

(*Received 3 December 2007; final version received 14 February 2008*)

With advances in information and communication technology, interactive multimedia learning systems are widely used to support teaching and learning. However, as human factors vary across users, they may prefer the design of interactive multimedia learning systems differently. To have a deep understanding of the influences of human factors, we apply a data mining approach to the investigation of users' preferences in using interactive multimedia learning systems. More specifically, a clustering technique named K-modes is used to group users' preferences. The results indicate that users' preferences could be divided into four groups where computer experience is a key human factor that influences their preferences. Implications for the development of interactive multimedia learning systems are also discussed.

Keywords: multimedia; human factors; data mining; clustering; K-modes

1. Introduction

With the emergence of advanced information and communication technologies, the interest in incorporating multimedia into instruction has increased. There has been a proliferation of interactive multimedia learning systems, which utilise several types of media, such as text, images, audio, animation and video, to attract a user's attention (Sun & Cheng, 2007). However, much remains to be learned about how different users perceive such systems. Users are unique and have a variety of human factors that greatly influence their learning patterns (Southwell, Anghelceva, Himelboima, & Jonesa, 2007). In this way, each user will appreciate such media differently, which will, in turn, determine whether they can successfully accept and use interactive multimedia learning systems (Antonietti & Giorgetti, 2006). Therefore to enhance the user's experience and satisfaction, human factors should be considered as an essential issue for the development of these systems. A number of learner-centred studies have shown that human factors have a strong impact on the use of learning technology (Chen & Macredie, 2004). An analysis of existing pedagogical studies also confirms that the successful usage of learning technology depends on the technology itself and the users' individual characteristics (Chou & Wang, 2000). For these reasons, a broad range of human factors have been examined

*Corresponding author. Email: Sherry.Chen@brunel.ac.uk

ISSN 1049-4820 print/ISSN 1744-5191 online

DOI: 10.1080/10494820801988315
http://www.informaworld.com

in previous studies, including age (Trentin, 2004), gender differences (Price, 2006), and levels of expertise (Mitchell, Chen, & Macredie, 2005).

While the results of these studies are useful, they mainly apply assumption-driven statistical techniques to analyse the empirical data in which hypotheses are formulated and then tested against the data. The problem of this approach is that the scope of results is restricted by the hypotheses. In other words, findings from data themselves may be ignored. On the other hand, data mining is able to uncover potentially useful information hidden in data (Bohen et al., 2003). Compared to traditional statistics, data mining is discovery driven in that it is not necessary to have the initial formulation of hypotheses and instead uses the data to discover patterns and relationships. In this paper, we apply a data mining approach to investigate the influences of human factors on users' preferences of an interactive multimedia learning system.

The paper is structured as follows: Section 2 presents theoretical background by analysing the problems of existing research in the field. Section 3 describes the methodology used to conduct the study and techniques applied to analyse the empirical data. Subsequently, the results of the study are presented and discussed in Section 4. Finally, conclusions based on our results are outlined in Section 5.

2. Theoretical background

In the past decade, a variety of information technologies have been applied to improve the quality of teaching and learning. In particular, many learning systems use interactive multimedia technologies (Asan, 2003). Unlike traditional learning systems, an interactive multimedia learning system is a rich environment, which uses various media and sophisticated techniques to provide advanced interface features, such as dynamic buttons and multiple windows. On the one hand, such interface features can help users freely navigate and easily identify relevant content (Hong, 2003). On the other hand, not all users appreciate the strengths of these interface features. This is due to the fact that diversity amongst users, referring to human factors such as gender differences and computer experience (Chen, 2005), makes them have different preferences. In other words, human factors play an important role in the use of interactive multimedia learning systems.

This issue has been investigated by a number of studies, which found that different groups of users demonstrate different learning preferences. Passig and Levin (1999) examined the gender differences in the preferences between varying designs of multimedia interfaces. The sample included 90 children from three kindergarten classes that used interactive multimedia stories. The research subjects responded to questions that elicited their level of satisfaction with the various interfaces. The findings of their study indicate that there is a significant difference in the level of satisfaction between boys and girls depending on the design of the user interfaces. Boys like the whole screen changes at once whilst girls dislike this approach. They also find that boys prefer green and blue colors, whilst the girls prefer red and yellow. Calisir and Gurel (2003) also investigated the interaction of three types of content structure – linear, hierarchical and mixed (hierarchical structure with cross referential links) – with prior knowledge of the user in hypermedia learning. Thirty participants, with half being classified as knowledgeable and half as non-knowledgeable, were used in the study. The results showed that a hierarchical content structure is most appropriate for non-knowledgeable subjects, probably because this structure provides a clear insight into the organisational framework of the subject content contained within the hypermedia system. Furthermore, Lin (2004) examined how older adults reacted to multimedia interfaces. Twenty-four older subjects participated in an experiment where presentation media and text topology were manipulated. The results indicated that multimedia built on organised links can lead the older user to better memory of the navigated information than the document based on a network of referential data connections.

While the results of these studies are useful, they merely apply statistical techniques to analyse the data. As such, they only represent the tip of the iceberg of what might be obtained by using advanced intelligent technologies, one of which is data mining. Data mining, also known as knowledge discovery (Fayyad & Uthurusamy, 1996), is an interdisciplinary area that encompasses techniques from a number of fields, including information technology, statistical analyses, and mathematic science (Bohen et al., 2003). A major function of data mining is to help analyse, understand or even visualise data stored in databases, data warehouses or other information repositories (Li & Shue, 2004). Based on the types of knowledge to be discovered, it can be broadly divided into unsupervised learning and supervised learning (Witten & Frank, 1999). The former is also known as clustering and the latter is also known as classification (Sander, Ng, Sleumer, Yuen, & Jones, 2005). Clustering is concerned with the division of data into groups of similar objects. Each group, called a cluster, consists of objects that are similar between themselves and dissimilar to objects of other groups. Wang, Chuang, Hsu, and Keh (2004) have developed a recommendation system for the cosmetic business. In the system, they segmented the customers by using clustering algorithms to discover different behaviour groups so that customers in the same group have similar purchase behaviour. Classification refers to assigning objects to predefined categories or classes. Brown et al. (2000), Mateos, Dopazo, and Jansen (2002) and Ng and Tan (2003) used classification to infer the functions of genes. Both clustering and classification are useful techniques but classification needs to have known categories or classes. A problem of analysing users' preferences with classification is that users are classified based on a particular human factor, instead of their preferences. If the human factor was not properly selected, the accuracy of the results might be affected. Therefore, we choose to use clustering in our study, which investigates how human factors are linked with users' preferences in interactive multimedia learning systems.

3. Methodology design

3.1. Participants

The study was conducted at a UK university. Initially, an email explaining the purpose of the study was sent to all students at the university. The email indicated that participants were required to have basic computing skills in order to take part in the study. A total of 80 students volunteered to participate in this study.

Among several human factors, the study focuses on the age, gender, level of expertise, and studying level of participants because previous research indicates that these factors have significant effects on users interaction (Czaja & Lee, 2001; Ford & Miller, 1996; Mitchell et al., 2005). According to the results of the first part of the questionnaire (see Section 3.2.2), the sample of participants was comprised of 50% males and 50% females. Seventeen per cent of users were aged between

16–20 years, 33% between 21–25 years, 24% between 26–30 years, 8% between 31–35 years, 6% between 36–40 years, and 12% aged above the age of 40. In respects of computer experience, 55% were classified as novices and 45% were experts. In respects of study levels, 38% were undergraduate, 23% were postgraduate, 18% were doctorate, and 21% were other qualifications.

3.2. *Research apparatus*

The research apparatus used in this study included: (1) interactive multimedia learning systems; (2) a questionnaire to identify users' preferences. The sections below explain the different research instruments used.

3.2.1. Interactive multimedia learning systems

To explore users' preferences, participants in this study were requested to interact with two interactive multimedia learning systems. On the one hand, these two interactive multimedia systems shared exactly the same content and adopted a quiz-style format to deliver general knowledge questions (for example sport, entertainment, and history). On the other hand, they were designed with different interaction styles, which allowed users to interact with the various types of multimedia elements and, in turn, users' preferences could be identified.

System A (Figure 1) adopted the WYSIWYG (What You See Is What You Get) interaction style, while System B (Figure 2) used the WIMP (Windows, Icons, Menus, Pointers) environment as its interaction style. These two interaction styles were chosen because they are commonly used in the creation of multimedia user

Figure 1. Screen layout of System A.

interfaces. The differences between these two interactive multimedia learning systems mainly lie within interface layout, button types, colour scheme, multimedia elements and menu formats. The details are illustrated in Table 1.

3.2.2. Questionnaire

A questionnaire, which has the potential to collect cognitive and affective data quickly and easily (Kinshuk, 1996), was applied to examine users' preferences of the interactive multimedia systems described in Section 3.2.1. The questionnaire

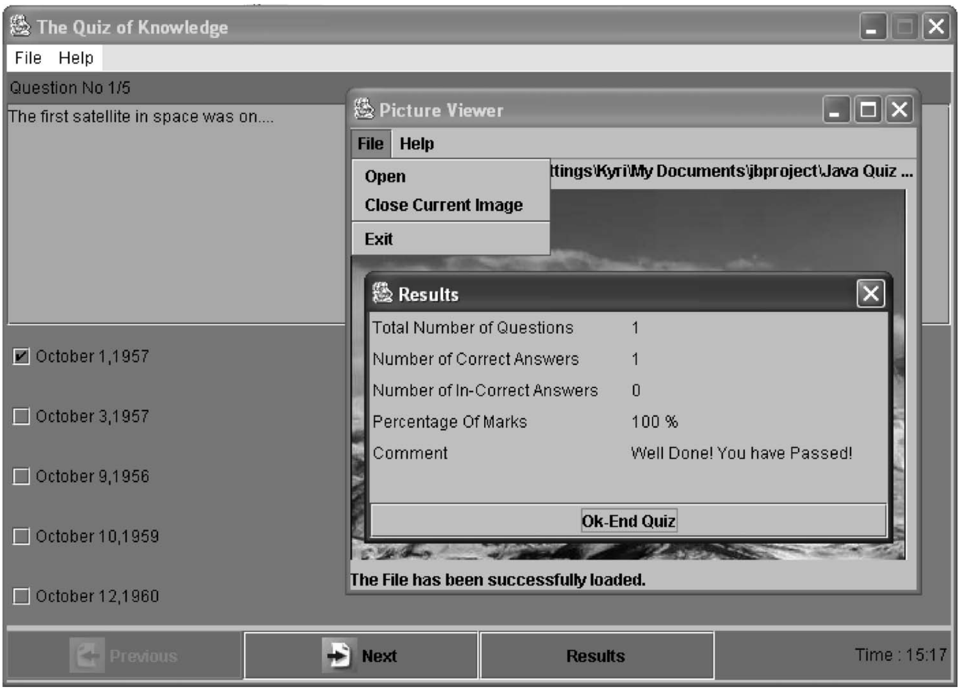

Figure 2. Screen layout of System B.

Table 1. The differences between the two interactive multimedia learning systems.

Interactive features	System A	System B
Interface layout	Single window	Multiple windows
Button types	Static (which do not give an indication, that is a colour change, when pressed), without embedded icons	Dynamic (which change colour or form when pressed), with embedded icons
Colour scheme	Multiple colours with the addition of effects, that is blending one colour into another.	Few standard colours
Multimedia elements	Images, graphics, audio and video	Images, graphics and audio
Menu formats	Without drop-down menus	Drop-down menus to access the help, images and audio

designed for the study was comprised of two parts. The first part, *Demographic information*, was used to identify users' personal details including age, gender, studying level and computer experience so as to obtain the individuals' human factors. With respects to age, individuals had the choice of selecting their age from six categories: 16–20 years, 21–25, 26–30, 31–35, 36–40, and above the age of 40. With respects to computer experience, users were instructed to indicate how often they used computers and software packages. Those who used computer and software packages more often were classified as experts, whereas those who used computer and software packages less often were classified as novices. With respect to study levels, users were classified as undergraduate, postgraduate, doctorate, and other qualifications.

The second part, *Learning preferences*, is the key part of the questionnaire. The differences presented in Table 1 provided the basic rationale for the design of this part of the questionnaire, which intended to capture users' preferences of a variety of interactive multimedia features found in both systems. More specifically, the users were required to select the interface features they favoured most from the choices offered by the two multimedia systems. The choices were in the form of categorical questions, with which each question could correspond to every multimedia interface feature used in the two systems. For example, the users were instructed to identify whether they preferred the use of either 'static buttons' or 'dynamic buttons' in multimedia learning systems. With this approach, the users most favoured interactive multimedia features could be easily identified.

3.3. Procedure

The study encompassed four steps. In order to avoid an order effect, half of the participants firstly completed the quiz in System A and then completed the quiz in System B. The other half of participants began to take the quiz in System B and then moved to the quiz in System A. The participants were observed during their interaction with the interactive multimedia learning systems and clarifications were given when required. Immediately after completing the quizzes with interactive multimedia learning systems, the participants were asked to answer the provided questionnaire.

3.4. Data analyses

3.4.1. Pre-processing of data

The data pre-processing stage predominantly involved feature selection. The features that did not relate to the users' preferences were excluded so that any deterioration with regards to the clustering of instances could be reduced (Fayyad, Piatetsky-Shapiro, & Smyth, 1996). For example, features which specifically related to the quiz, such as the type of questions or results feedback preferred by users, were excluded. As a result, the selected features corresponded to the different multimedia features provided by the two interactive multimedia learning systems (Table 1). Thus, the final set of features comprised of: (1) the layout of the interface; (2) the button type preferred by users; (3) the use of icons embedded within buttons; (4) the use of menus; and, (5) user's preferred colour scheme.

3.4.2. K-modes algorithm

Among a plethora of clustering algorithms, the K-means algorithm is a widely known and used technique for grouping objects with similar characteristics, mainly due to its computational efficiency (Jain, Murty, & Flynn, 1999). The K-modes algorithm is an extension of K-means algorithm, used to cluster data containing mixed numeric and categorical values (Huang, 1998). The K-modes algorithm uses a simple matching dissimilarity measure to deal with categorical objects, replaces the means of clusters with modes, and uses a frequency-based method to update modes in the clustering process to minimise the clustering cost function. With these extensions, the K-modes algorithm enables the clustering of categorical data in a fashion similar to K-means. Such extensions are useful for analysing data of this study because the data obtained through the questionnaire are categorical.

Like K-means, the K-modes algorithm requires the number of clusters (k) and the seed (s), which generates the values for the assignment of the initial cluster centres, to be fixed a priori. Since the algorithm is sensitive to how clusters are initially assigned (Khan & Ahmad, 2004), it is necessary to try different values and evaluate the results in order to find the combination that better fits the data. This is because different runs of the algorithm, that is changing k and s, yield different results. Consequently, different combinations of the previously mentioned attributes were used to evaluate results for the best performance of the algorithm. Having exhausted several combinations, the results showed that the algorithm produces more meaningful outcomes when $k = 4$ and $s = 10$.

4. Results and discussion

4.1. Interactive multimedia features

The clustering of users has shown a definitive division between their preferences of interactive multimedia features. Table 2 illustrates the meaning of each cluster with regards to users' preferences of features found in both interactive multimedia learning systems. The chosen features indicate that participants are grouped according to the following trends: (1) Cluster 1: users prefer the single window interface that utilises static buttons with no embedded icons and no use of drop-down menus though they favour the colours with effects background; (2) Cluster 2: users prefer the multiple window layout, as opposed to users in Cluster 1, use dynamic buttons with embedded icons and favour drop-down menus along with the standard colour scheme; (3) Cluster 3: users similarly favour the single window interface as in Cluster 1, prefer static buttons with embedded icons and the multicoloured background scheme,

Table 2. The differences between the four clusters.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Interface layout	Single window	Multiple windows	Single window	Multiple windows
Button type	Static	Dynamic	Static	Dynamic
Use of icons	No	Yes	Yes	No
Use of menus	No	Yes	No	No
Colour scheme	Colours with effects scheme	Standard colour scheme format	Multiple colour scheme	Colours with effects scheme

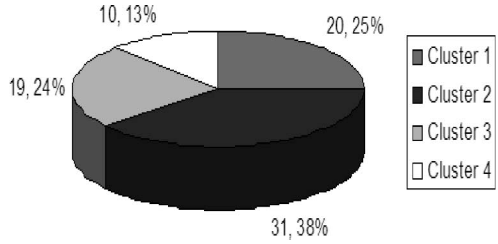

Figure 3. The number of users in each cluster.

though they do not like the drop-down menus; and (4) Cluster 4: users similarly prefer the multiple window interface with dynamic buttons that do not contain icons, do not use drop-down menus and, favour the colours with effects style.

As depicted in Figure 3, many users appear in Cluster 2 and few emerge in Cluster 4. The main differences between Cluster 2 and Cluster 4 lie within the use of icons, drop-down menus, and colour schemes. The users in the former prefer dynamic buttons with embedded icons, drop-down menus, and like the standard colour scheme, while those in the latter favour dynamic buttons without icons, dislike drop-down menus, and prefer the colours with effects format.

As mentioned above, Cluster 2 consists of more users (N = 31, 38%) than the remaining three clusters. The key difference between Cluster 2 and the other clusters is that the users in this cluster favour a single colour scheme. This suggests that the single colour scheme is most popular with users. In contrast, multiple colours and colours with effects are found to be less popular with users. These results are compatible with the cognitive load theory (Sweller, van Merriënboer, & Paas, 1998), which suggests that the focus of an instructional module must be the instruction itself. Information adjunct to the instruction must be designed to minimise cognitive load (Feinberg & Murphy, 2000). In this study, the single colour scheme may in turn increase the user's concentration on the instruction itself. On the other hand, multiple colours and colours with effects could promote distraction and unnecessary clutter to the user's mind and exacerbate cognitive load as well as associated mental energy. This may explain why most users prefer the single colour scheme, instead of multiple ones and colours with effects.

Moreover, Cluster 4 has the least number of users (N = 10, 13%). Users in Cluster 4 prefer the multiple window layout, dynamic buttons, and the colours with effects scheme. This may suggest that the integration of these interactive multimedia features offer users a pleasant visual display with multiple colour presentation. By examining the demographic information of these 10 users, it is interesting to see that all are females. A noticeable difference between females and males is that female users particularly favour appealing images as a means of presenting information (Miller & Arnold, 2000). This difference may be able to explain the reason why female users prefer interactive multimedia learning systems with attractive visual displays, as illustrated by their preferences showed in Cluster 4.

4.2. The effects of human factors

In order to identify the role of human factors on determining the clusters, ANalysis Of VAriance (ANOVA) was used to obtain statistical significance of age, studying level, computer expertise, and gender differences. The results indicate that computer experience (F (3,76) = 4.19; $p < 0.05$) was a significant factor in determining the clusters representing users' preferences. Figure 4 illustrates the proportion of experts and novices within each cluster. The majority of experts (N = 30, 83%) appeared in Cluster 2 and Cluster 4 whereas novices (N = 33, 75%) mainly emerged in Cluster 1 and Cluster 3. Detailed results are presented below.

4.2.1. *Window layouts*

A difference between Clusters 2/4 and Clusters 1/3 is that the users in Clusters 2/4 like multiple windows (referring to System B) while those in Clusters 1/3 prefer a single window layout (referring to System A). It suggests that novices prefer a single window layout whereas experts prefer a multiple window layout. In other words, one's computer experience can dramatically affect his/her preferences of interface layout. Analyses of frequency also reveal that the single window layout is favoured by 66% (N = 29) of novices while the multiple window layout is preferred by 64% (N = 23) of experts (Table 3). The result of ANOVA also indicated that computer experience significantly affects the users' preferences of interface layout (F (3,76) = 4.52; $p < 0.01$).

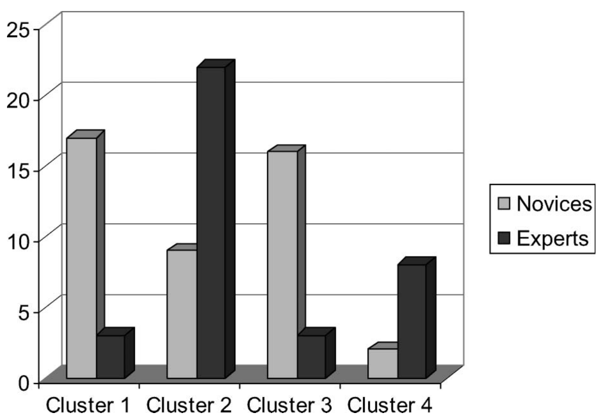

Figure 4. Levels of computer experience in each cluster.

Table 3. Preferences of novices and experts.

Interactive multimedia learning systems		Novices *N*	Novices %	Experts *N*	Experts %
Window layouts	Single	29	66	13	36
	Multiple	15	34	23	64
Navigation buttons	Static	23	52	1	3
	Dynamic	21	48	35	97
Drop-down menu	Like	18	41	33	92
	Dislike	26	59	3	8

Such findings echo previous work by Smith et al. (1999), which found that computer experience may affect one's motivation when using the system. Novices have greater difficulty in assimilating interfaces they have previously never seen, so they may prefer interface features that do not require them to heavily rely on their prior expertise or knowledge of similar situations, therefore reducing computer anxiety and task negativity, in order to complete the current task in hand. However, experts are individuals who have gained more theoretical insight and a number of guiding principles to infer ambiguous computer scenarios (Beckers, Rikers, and Schmidt, 2006) so that they might feel comfortable interacting with more complicated interface layouts, such as multiple windows.

4.2.2. Navigation tools

Navigation buttons and main menus are two major navigation tools utilised in interactive multimedia learning systems. According to our results, the preference of navigation buttons is another difference between Clusters 2/4 and Clusters 1/3. The static button is favoured by users in Clusters 1/3, whereas the dynamic button is preferred by the users in Cluster 2/4. The other difference between Clusters 2/4 and Clusters 1/3 is the use of drop-down menus. The drop-down menus are favoured by the users in Clusters 2/4, instead of those in Clusters 1/3. In other words, the majority of experts favour using dynamic buttons and the drop-down menus while novices like static buttons and dislike drop-down menus. Analyses of frequency also indicate that 97% (N = 35) of experts prefer the dynamic buttons while 52% (N = 23) of novice favour the static buttons (Table 3). Moreover, 92% (N = 33) of experts like drop-down menus while 59% (N = 26) of novices do not favour this feature (Table 3). The result of ANOVA also indicated that computer experience has significant effects on users' preferences of dynamic/static buttons (F (3,76) = 11.58; $p < 0.001$) and drop-down menus (F (3,76) = 9.56; $p < 0.001$).

A possible reason for such findings is that dynamic buttons and drop-down menus belong to more advanced interactive multimedia features, which are beneficial to experts. However, these features may not be useful to novices who have little or no formal training and experience (Simmons & Lunetta, 1993). These results are in line with those of Hasan (2003), which found that individuals perceive themselves at a disadvantage when they do not have sufficient computer experience to enable them to complete their task. It may be due to the fact that novices exhibit higher levels of anxiety (Beckers et al., 2006), possibly because of unfamiliarisation with a system, which can affect the way in which they used the interactive multimedia learning system.

5. Concluding remarks

The study presented in this paper adopted a data mining approach to uncover relationships between human factors and users' preferences in interactive multimedia learning systems. Overall results revealed a prominent division between diverse types of users, as shown by their varied preferences across clusters where computer experience had considerable effect on preferences. More specifically, experts favour dynamic buttons and multimedia windows and like to use drop-down menus, while novices prefer static buttons and a single window and dislike drop-down menus. These results reinforce the findings of previous research that indicated experts and novices favoured different types of features provided by interactive multimedia learning systems. Our findings, as well as those in previous research can be integrated to develop personalised interactive multimedia learning systems that can accommodate the needs and preferences of different users. By doing so, users will have an equal opportunity of using and benefiting from interactive multimedia learning systems (Joiner, Littleton, Chou, & Morahan-Martin, 2006).

Nonetheless, this is only a small-scale study. Further work needs to be undertaken with a larger sample to provide additional evidence. Moreover, it would be interesting to analyse users' preferences with other clustering techniques, such as Hierarchical Clustering or Self-Organising Maps, or classification techniques such as Decision Trees or Support Vector Machines. It would be interesting to see whether similar results will be found by using these methods.

Notes on contributors

Kyriacos Chrysostomou is a PhD student in the School of Information Systems, Computing and Mathematics, Brunel University, Uxbridge, U.K. His current research interests include human–computer interaction, data mining, classification and feature selection.

Sherry Y. Chen is a Reader in the School of Information Systems, Computing and Mathematics at Brunel University. She obtained her PhD from the Department of Information Studies, University of Sheffield, UK in 2000. Her current research interests are human–computer interaction, data mining, digital libraries, and educational technology. She has published widely in these areas. Dr. Chen is the editor of several research books, including Adaptable and Adaptive Hypermedia Systems and Advances in Web-based Education: Personalized Learning Environments. She is a member of the editorial boards of seven computing journals.

Xiaohui Liu is Professor of Computing at Brunel University where he directs the Centre for Intelligent Data Analysis, conducting interdisciplinary research concerned with the effective analysis of data. He was the founding chair of the international conference series on IDA (1995), a keynote speaker at the International Conference of the Royal Statistical Society (2002), and vice chair of the IEEE International Conference on Data Mining (2004). Professor Liu has over 200 refereed publications in data mining, bioinformatics, intelligent systems and time series. He was appointed as Honorary Pascal Professor at Leiden University in the Netherlands in 2004.

References

Antonietti, A., & Giorgetti, M. (2006). Teachers' beliefs about learning from multimedia. *Computers in Human Behavior*, *22*(2), 267–282.

Asan, A. (2003). School experience course with multimedia in teacher education: An example from Turkey. *Journal of Computer Assisted Learning*, *19*(1), 21–34.

Beckers, J., Rikers, R., & Schmidt, H. (2006). The influence of computer anxiety on experienced computer users while performing complex computer tasks. *Computers in Human Behavior*, *22*(3), 456–466.

Bohen, S.P., Troyanskaya, O.G., Alter, O., Warnke, R., Botstein, D., Brown, P.O., & Levy, R. (2003). Variation in gene expression patterns in follicular lymphoma and the response to rituximab. *Proceedings of the National Academy of Sciences*, *100*(4), 1926–1930.

Brown, M.P.S., Groundy, W.N., Lin, D., Cristianini, N., Sugnet, C.W., Furey, T.S., Ares, M. Jr., & Haussler, D. (2000). Knowledge based analysis of microarray gene expression data by using support vector machines. *Proceeding of the National Academy of Sciences*, *97*(1), 262–267.

Calisir, F., & Gurel, Z. (2003). Influence of text structure and prior knowledge of the learner on reading comprehension, browsing and perceived control. *Computers in Human Behavior*, *19*(2), 135–145.

Chen, S.Y. (2005). Evaluating the learning effectiveness of using web-based instruction: An individual differences approach. *International Journal of Information & Communication Technology Education*, *1*(1), 69–82.

Chen, S.Y., & Macredie, R.D. (2004). Cognitive modelling of student learning in web-based instructional programmes. *International Journal of Human-Computer Interaction*, *17*(3), 375–402.

Chou, H., & Wang, T. (2000). The influence of learning style and training method on self-efficacy and learning performance in WWW homepage design training. *International Journal of Information Management*, *20*(6), 455–472.

Czaja, S.J., & Lee, C.C. (2001). The internet and older adults: Designs challenges and opportunities. In N. Charness & D.C. Parks (Eds.), *Communication, and aging: Opportunities and challenges for the future* (pp. 60–78). New York: Springer.

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases: A survey. *AI Magazine*, *17*(3), 37–54.

Fayyad, U., & Uthurusamy, R. (1996). Data mining and knowledge discovery in databases. *Communications of the ACM*, *39*(11), 24–26.

Feinberg, S., & Murphy, M. (2000). Applying cognitive load theory to the design of web-based instruction. In Proc. of IEEE Professional Communication Society international Professional Communication Conference and Proc. of the 18th Annual ACM International Conference on Computer Documentation: Technology & Teamwork (pp. 353–360). Cambridge, MA.

Ford, N., & Miller, D. (1996). Gender differences in internet perceptions and use. *Aslib Proceedings*, *48*, 183–192.

Hasan, B. (2003). The influence of specific computer experiences on computer self-efficacy beliefs. *Computers in Human Behavior*, *19*(4), 443–450.

Hong, X. (2003). Supporting ease-of-use and user control: Desired features and structure of web-based online IR systems. *Information Processing & Management*, *39*(6), 899–922.

Huang, Z. (1998). Extensions to the K-means algorithm for clustering large data sets with categorical values. *Data Mining and Knowledge Discovery*, *2*, 283–304.

Jain, A.K., Murty, M.N., & Flynn, P.J. (1999). Data clustering: A review. *ACM Computing Surveys*, *31*(3), 264–323.

Joiner, R., Littleton, K., Chou, C., & Morahan-Martin, J. (2006). Gender and information communication technology. *Journal of Computer Assisted Learning*, *22*(5), 317–319.

Khan, S., & Ahmad, A. (2004). Cluster center initialization algorithm for *K*-means clustering. *Pattern Recognition Letters*, *25*(11), 1293–1302.

Kinshuk. (1996). *Effectiveness of intelligent tutoring tools interfaces in relation to student, learning topic and curriculum characteristics*. Unpublished doctoral dissertation, De Montfort University, UK.

Li, S., & Shue, L. (2004). Data mining to aid policy making in air pollution management. *Expert Systems and Applications*, *27*(3), 331–340.

Lin, D.M. (2004). Evaluating older adults' retention in hypertext perusal: Impacts of presentation media as a function of text topology. *Computers in Human Behavior*, *20*(4), 491–503.

Mateos, A., Dopazo, J., & Jansen, R. (2002). Systematic learning of gene functional classes from DNA array expression data by using multilayer perceptrons. *Genome*. *Research*, *12*(11), 1703–1715.

Miller, H., & Arnold, J. (2000). Gender and web home pages. *Computers & Education*, *34*(3/4), 335–339.

Mitchell, T.J.F., Chen, S.Y., & Macredie, R.D. (2005). Hypermedia learning and prior knowledge: Domain expertise vs. system expertise. *Journal of Computer Assisted Learning*, *21*, 53–64.

Ng, S., & Tan, S. (2003). On combining multiple microarray studies for improved functional classification by whole-dataset feature selection. *Genome Informatics*, *14*, 44–53.

Passig, D., & Levin, H. (1999). Gender interest differences with multimedia learning interfaces. *Computers in Human Behavior*, *15*, 173–183.

Price, L. (2006). Gender differences and similarities in online courses: Challenging stereotypical views of women. *Journal of Computer Assisted Learning*, *22*(5), 349–359.

Sander, J., Ng, R.T., Sleumer, M.C., Yuen, M.S., & Jones, S.J. (2005). A methodology for analyzing SAGE libraries for cancer profiling. *ACM Transactions on Information Systems*, *23*, 35–60.

Simmons, P.E., & Lunetta, V.N. (1993). Problem-solving behaviors during a genetics computer simulation: Beyond the expert/novice dichotomy. *Journal of Research in Science Teaching*, *30*(2), 153–173.

Smith, B., Caputi, P., Crittenden, N., Jayasuriya, R., & Rawstorne, P. (1999). A review of the construct of computer experience. *Computers in Human Behavior*, *15*(2), 227–242.

Southwell, B.G., Anghelceva, G., Himelboima, I., & Jonesa, J. (2007). Translating user control availability into perception: The moderating role of prior experience. *Computers in Human Behavior*, *23*(1), 554–563.

Sun, P., & Cheng, H. (2007). The design of instructional multimedia in e-Learning: A media richness theory-based approach. *Computers & Education*, *49*(3), 662–676.

Sweller, J., van Merriënboer, J.J.G., & Paas, F. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, *10*(3), 251–296.

Trentin, G. (2004). E-learning and the third age. *Journal of Computer Assisted Learning*, *20*(1), 21–30.

Wang, Y., Chuang, Y., Hsu, M., & Keh, H. (2004). A personalized recommender system for the cosmetic business. *Expert Systems with Applications*, *26*(3), 427–434.

Witten, I.H., & Frank, E. (1999). *Data mining. Practical machine learning tools and techniques with JAVA implementations*. San Francisco: Morgan Kaufman Publishers.