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Mining User Preferences of Multimedia Interfaces with K-modes

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Abstract—**Interactive multimedia learning systems use sophisticated techniques to present advanced interface features. However, not all users appreciate the strengths of such interface features because of the variations of user backgrounds and skills. In this context, human factors are important issues in deciding user preferences. This study applies a data mining approach to examine user preferences of interface features and to identify the influence of human factors on this issue. K-modes, a data mining technique extensively applied to user modeling, was used to group users' preferences. The results indicated that users' preferences could be divided into eight groups where gender and computer experience significantly influenced the choices made by users.**

I. Introduction

With the advance of multimedia technologies, there has been a proliferation of interactive learning systems, which utilize various media, such as text, images, audio, animation and video [37]. Unlike traditional learning systems, an interactive multimedia learning system is a rich environment, which uses 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 [17]. On the other hand, not all users appreciate the strengths of these interface features. This is due to the fact that variations within users, referring to human factors such as age, gender, capabilities, and computer experience [3], make them have diverse preferences of interface features.

The diversity in the user population results is a new challenge for interface design. In response to this challenge, more attention needs to be directed to see which human factors significantly affect user preferences of interface features when interacting with interactive multimedia learning systems. In this sense, the human factors that determine user preferences can be used to personalize multimedia interfaces. Therefore, such investigation can potentially provide insight for designers, assisting them in redesigning and restructuring the layout and content of multimedia interface, in order to accommodate the needs of diverse users [26]. To this end, this study aims to examine user preferences of interface features and to identify the role of human factors on their preferences.

This issue has been investigated by a number of studies, which found that different groups of users preferred different functionalities and configurations provided by multimedia interfaces [12][10][32]. The results of studies in [33] indicated that males and females use different means for navigation purposes, [29] found that experts have more positive perceptions to non-linear navigation than individuals with less computer expertise, and [6] found older adults to have less computer experience and higher anxiety than their younger counterparts, which can affect overall computer interaction. While the results of these studies are useful, they merely apply statistical techniques to analyze 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 [9], is an interdisciplinary area that encompasses techniques from a number of fields, including information technology, statistical analyses, and mathematic science [2]. A major function of data mining is to help analyze, understand or visualize the huge amounts of data stored in databases, data warehouses, or other information repositories [25]. Recent studies suggest that data mining is a useful tool for analyzing user preferences [7][23] because it can discover regularities and patterns hidden in data [5][30]. Therefore, we chose to use data mining to analyze user preferences of interface features in an interactive multimedia learning system.

Based on the nature of information extraction, data mining approaches can be broadly divided into three major categories [4]: (1) clustering, which finds groups of similar objects sharing a number of properties, (2) classification, which is used to categorize a data item into one of several predefined classes, and (3) association rules, which reveal the nature and frequency of relationships between data objects [4][8]. For the purpose of this study, clustering was chosen due to its ability to group users that share common preferences [15]. Thus, the problem of identifying user preferences of interface features in the interactive multimedia learning system can also benefit from this technique by identifying groups of individuals with similar preferences. Among a range of clustering techniques, the K-modes algorithm, which was effectively used in similar problems [20], was employed in this study to produce groups of users that shared similar preferences of interface features. Subsequently, the corresponding human factors for each group were identified.

The paper is structured as follows. Section 2 describes the experiment run to collect users' preferences. Section 3 presents the technique used to analyze the data, i.e. K-modes algorithm. Subsequently, the grouped users' preferences are illustrated in Section 4, where the relation between the clusters and the human factors is presented. Finally, conclusions are drawn and possibilities for future work are identified in Section 5.

II. Experimental Design

This section details the participants of the experiment along with the research instruments used.

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TABLE I DIFFERENCES BETWEEN THE TWO MULTIMEDIA INTERFACES

Interactive Features	Interface A	Interface B
Interface Layout	Single window	Multiple windows
Button Types	Static, without embedded icons	Dynamic, with embedded icons
Color Scheme	Numerous colours and the use of effects, i.e. blending one color 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

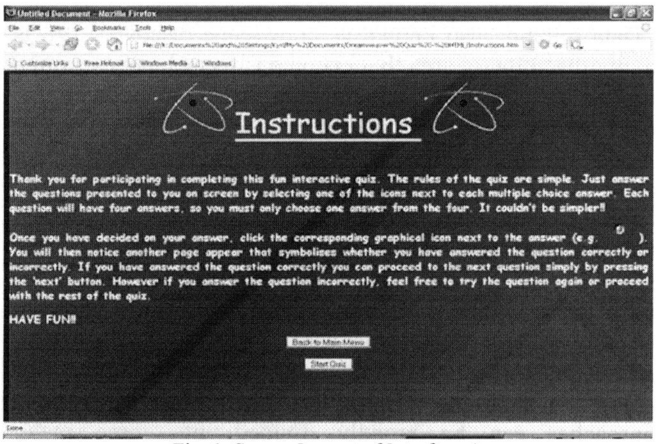

Fig. 1 Screen Layout of Interface A

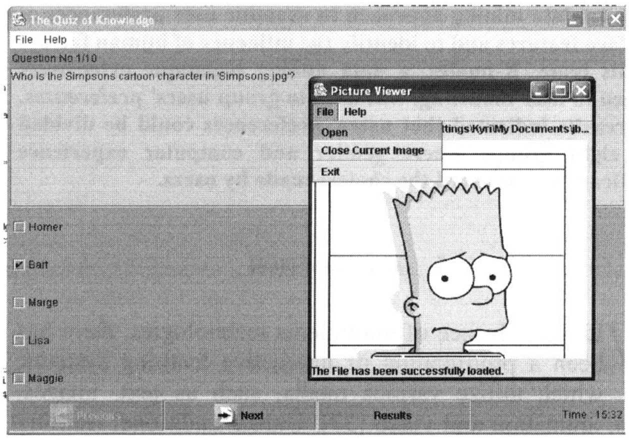

Fig. 2 Screen Layout of Interface B

A. Participants

The study was conducted at Brunel University. Eighty participants took part in the experiment, where all had basic computing skills necessary to run the experiment.

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 [6], [10], and [29]. The sample of participants comprised of 50% males and 50% females. Individuals had the choice of selecting their age from six categories: 16 to 20, 21 to 25, 26 to 30, 31 to 35, 36 to 40, and above 40. Within the dataset, 17% of users were aged between 16 and 20, 33% between 21 and 25, 24% between 26 and 30, 8% between 31 and 35, 6% between 36 and 40, and 12% aged above the age of 40. The level of computer experience was also defined using two categories: intermediate and expert, where 57% had intermediate computer experience and 43% were classed as experts. Finally, participants' studying level was recorded into one of the following four categories: undergraduate (38%), postgraduate (23%), doctorate (18%), and other qualifications (21%).

B. Research Instruments

This section describes the interfaces used by participants and the questionnaire intended to capture users' preferences.

1) Interfaces

The interface was the most important aspect as it determined the way of accessing information. To explore how users access information via the interface, participants in this experiment were requested to interact with two interactive multimedia 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 (e.g. 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 interface elements and, in turn, users' preferences could be identified.

Interface A (Fig. 1) adopted the WYSIWYG (What You See Is What You Get) interaction style, while Interface B (Fig. 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 interfaces. The differences between these two interactive multimedia learning systems mainly lie within interface layout, button types, color scheme, multimedia elements, and menu formats. The details are illustrated in Table I. For example, two types of buttons were used; including static (which do not give an indication, i.e. a color change, when pressed) and dynamic (which change color or form when pressed).

TABLE II SEMANTICS OF EACH CLUSTER
MW = MULTIPLE WINDOWS, SW = SINGLE WINDOW, MCS = MULTIPLE COLOR SCHEME, SCS = STANDARD COLOR SCHEME AND CWES = COLORS WITH EFFECTS SCHEME

	Interface Layout	Button Type	Use of Icons	Use of Menus	Colour Scheme	% of Users
C1	MW	Static	No	No	MCS	5
C2	MW	Dynamic	Yes	Yes	SCS	28
C3	SW	Dynamic	Yes	Yes	MCS	14
C4	MW	Dynamic	No	No	CWES	6
C5	SW	Static	Yes	No	CWES	25
C6	MW	Dynamic	Yes	Yes	MCS	11
C7	SW	Dynamic	Yes	Yes	SCS	5
C8	SW	Dynamic	Yes	Yes	CWES	6

2) Questionnaire

The questionnaire designed for the experiment comprised of two parts. The first part, Demographic Information, was to identify users' personal details, including age, gender, computer experience, and studying level so as to obtain the individuals' human factors. The second part, User Preferences, is the key part of the questionnaire. This part consisted of categorical questions that examined users' preferences for various multimedia interface features, presented in Table I. In other words, the differences presented in Table I provided the basic rationale for the design of the questionnaire, which intended to capture users' preferences of a variety of multimedia features found in both interfaces.

3) Experiment Procedure

The experiment encompassed four stages:

1. The participant completed the quiz in Interface A.
2. The participant then completed the quiz in Interface B.
3. Participants were observed during their interaction and clarifications were given when required.
4. Immediately after the activity, participants were asked to answer the provided questionnaire.

4) Data Collection and Summarisation

The vector used for representing the preferences of each user contained the following dimensions: (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) their preferred color scheme. These are further explained in Table I.

III. K-MODES CLUSTERING

The goal of clustering is to partition a given set of unlabelled and unclassified instances, based on similarities within the training data, into meaningful clusters [21]. Typically, a clustering algorithm finds the set of clusters that covers all instances so that the similarity between instances of the same clusters is maximized, and the similarity between instances of different clusters is minimized.

There are various types of clustering algorithms, among which the K-means algorithm is a widely known and used *partitional* or *nonhierarchical* clustering technique, mainly due to its computational efficiency [22]. The K-modes algorithm is an extension of K-means, which can be used to cluster data containing categorical values [18]. 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 [19].

Like K-means, the K-modes algorithm consists of a re-estimation procedure in order to cluster a given data set through a certain number of k clusters fixed a priori. The aforementioned extensions minimise the following objective function:

$$J(Z,X)=\sum_{l=1}^{k}\sum_{i=1}^{n}d_c(Z_l,X_i) \tag{1}$$

where k is a positive integer representing a known number of clusters, n represents the number of items in the data set, and $d_c(Z_l,X_i)$ is the matching dissimilarity measure between Z_l (the mode of a cluster) and X_i (an item) defined as,

$$d_c(Z_l,X_i)=\sum_{j=1}^{m}\delta(z_{lj},x_{ij}) \tag{2}$$

subject to

$$\delta(z_{lj},x_{ij})=\begin{cases}0 & (x_{lj}=z_{lj}),\\ 1 & (x_{lj}\neq z_{lj})\end{cases} \tag{3}$$

where m is the dimension of the items and each dimension represents a categorical attribute. The above dissimilarity value is *0* when two objects are identical or *1* when they are not. In addition, Z represents a set of k (m-dimensional) modes for k clusters. That is, the mode for a set of categorical objects $\{X_1,X_2,\ldots,X_n\}$ is defined as an object Z that minimizes $\sum_{i=1}^{n} d_c(X_i,Z)$.

The K-modes algorithm clusters categorical data in the following way:

1. k m-dimensional modes are selected as input, so that there is one for each cluster.

2. An object is designated to a cluster whose mode is the nearest according to the objective function (1). The mode of the cluster is then updated after each allocation.
3. After all objects have been assigned to clusters, the dissimilarity of objects is retested against the current modes. If an object is found such that its nearest mode belongs to another cluster rather than its current one, the object is reallocated to that cluster and the modes of both clusters are updated.
4. The previous step is repeated until there is no change in the assignment of objects to clusters.

K-modes, like K-means, is sensitive to the initial partition, i.e. the selection of the initial centers, and may converge to a local minimum of the criterion function value if the initial partition is not appropriately chosen. A possible solution is to run the algorithm numerous times with a number of different initial partitions, i.e. to change seed values.

In the context of user modelling, K-means/K-modes have proven to be very useful in finding groups of users that share common preferences or groups of users that share a common perception. For example, [20] uses K-modes to model web access sessions as a way of modelling user behavior and [23] utilizes K-means to group user's with regards to their television viewing behaviour. Further studies have also been conducted [7][13][27][35]. Hence by clustering users, groups of users exhibiting similar preferences or behaviour can be established.

IV. RESULTS OF EMPIRICAL STUDY

The WEKA software [38] tool was used to apply K-modes to the preference data and SPSS (for Windows) was used to discover the role of human factors on cluster formation.

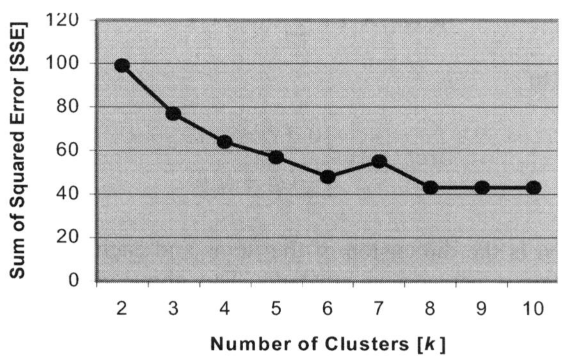

Fig. 3. The SSE when $k = 2,\ldots,10$

A. Clustering Users' Preferences

The data of user preferences were fed into K-modes. In order to determine the optimum number of clusters the algorithm was run for $k = 2,\ldots,10$. To avoid K-modes, for a given k, reaching a local minima due to the randomness of the original centers, the algorithm was run for each value of k with twelve different seeds. However, it was found that altering the seed did not affect the clustering of users. Fig. 3 shows the sum of squared error (SSE) value when the number of clusters, k, is varied. As the optimum solution is the one that minimizes the objective function J presented in (1), we can see from Fig. 3 that the lowest SSE was when k ranged from 8 to 10. Thus, choosing the lowest value for k, i.e. 8, the original data was divided into 8 clusters.

Table II illustrates the semantics of each cluster with regards to the users' preferences for interface features found in both multimedia systems. Take Cluster 1 as an example: Users in this cluster preferred the multiple window layout that utilized static buttons with no embedded icons, no use of drop-down menus and favored the multicolored background scheme.

TABLE III SIGNIFICANCE VALUES WHEN K IS 8

	$k = 8$
Gender	F=6.002, p=.000
Age	F=0.552, p=0.792
Studying Level	F=1.206, p=0.310
Computer Experience	F=4.773, p=.000

To examine the number of users in each cluster, we found that Cluster 2 has the most number (N=28) of users whereas Cluster 1 and Cluster 7 are the clusters which have the fewest number (N=5). However, users within Cluster 2 and Cluster 7 preferred identical interface features except for the type of window layout. The former preferred the multiple window layout while the latter favored the single window layout. It implies that the multiple window layout is more popular than a single window layout probably because presenting information in more than one window or by dividing one window into two or more sections enables the user to easily switch between displays [14]. This finding echoes the result of [34], in which multiple windows that can be resized and put aside as smaller windows have been found to be more effective than single static windows.

B. Influence of Human Factors

In order to identify the role of human factors on determining the clusters, ANalysis Of VAriance (ANOVA) was used to obtain the significance values of Age, Studying Level, Computer Expertise, and Gender when k was 8. This is illustrated in Table III. The ANOVA revealed no significant effect of age and studying level on the grouping of users that share common preferences. In contrast, gender differences ($p<0.05$) and computer experience ($p<0.05$) were factors shown to be statistically significant in determining the clusters representing user preferences. Based on these two significances, the proportion of males and females, experts and intermediate users within each cluster are identified in Table IV. In this table, '% in cluster' refers to the % of a human factor in a cluster, while '% in sample' refers to the % of a human factor in the entire sample. The subsequent subsections discuss the influences of computer experience and gender differences on users' preferences.

TABLE IV DIFFERENCES IN GENDER AND LEVEL OF COMPUTER EXPERIENCE

	Gender				Computer Experience			
	Male		Female		Intermediate		Expert	
	% in cluster	% in sample	% in cluster	% in sample	% in cluster	% in sample	% in cluster	% in sample
Cluster 1	-	-	100	10	100	9	-	-
Cluster 2	77	43	23	12.5	32	16	68	42
Cluster 3	55	15	45	12.5	55	14	45	14
Cluster 4	-	-	100	12.5	60	7	40	5
Cluster 5	20	10	80	40	95	43	5	3
Cluster 6	89	20	11	2.5	33	7	67	17
Cluster 7	75	7	25	2.5	25	2	75	8
Cluster 8	40	5	60	7.5	20	2	80	11

1) *Computer Experience*

As shown in Table II, Cluster 2 has the most number of users (N=28) and Cluster 5 has the second most number (N=25). By further examining Table IV, it is evident that Cluster 2 groups approximately half of the expert users (42%) in the sample, while Cluster 5 groups approximately half of intermediate users (43%). The differences between Cluster 2 and Cluster 5 are that the users in the former favored multiple windows, dynamic buttons, and drop-down menus while the latter did not appreciate these features. In other words, the majority of experts favored using multiple windows, dynamic buttons and drop-down menus while those with intermediate experience preferred a single window, static buttons and disliked using drop-down menus. This in turn illustrates that multiple windows, dynamic buttons and drop-down menus belong to more advanced interface features that are beneficial to experts, though they may not be useful to intermediate users who have less experience. These results are in line with those of [12], which found that individuals perceive themselves at a disadvantage when they do not have sufficient computer experience or training to enable them to complete their tasks. It may be due to the fact that individuals with lower system expertise have high levels of anxiety [1][24], possibly due to unfamiliarisation with a system, which can affect task efficacy and their overall adoption of technology.

To analyze the details of each interface feature, we found that static buttons were favored by users in Clusters 1 and 5 whereas dynamic buttons were preferred by users in the remaining six clusters, who were found to have higher levels of computer expertise. In addition, drop-down menus were favored by users in Clusters 2, 3, 6, 7, and 8, the majority of which were experts, though not by users in Cluster's 1, 4, and 5 who had intermediate computer experience. Such evidence suggests that computer experience affects user preferences of interface features. A possible explanation might be that users with lower computer experience have greater difficulty in assimilating interfaces they have previously never seen due to their lack of prior experience. They may therefore 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 [36]. However, experts are individuals who have gained more theoretical insight and a number of guiding principles to infer ambiguous computer scenarios [16], so they should feel more comfortable to interact with more complicated interface layouts, e.g. multiple windows.

2) *Gen*der Differences

Focusing on gender differences across clusters, a clear divide in user preferences appears, especially for the use of colors. The majority of users, represented by Cluster 2, favored a single color scheme. However, a significant amount of individuals in Cluster 5 preferred the colors with effects format. Further investigation of user demographics reveals that the majority of users in Cluster 2 are males (77%) as opposed to Cluster 5 being dominated by females (80%). Such results show that a number of males preferred Interface B that used fewer colors, compared to females who favored Interface A where numerous colors were utilized. A possible explanation for this may be that females, who tend to experience more difficulty when interacting with computers compared to males [10][11], prefer the use of several colors as a means of maintaining their interest in the task at hand. The other evidence is that users in Cluster 4 favored the colors with effects scheme. In this cluster, all users were females. This potentially implies that females might prefer multimedia interfaces that incorporate a pleasant visual display by using attractive graphics or the use of several complementary colors. These results are in agreement with those of [28], which found that females particularly favored appealing images used as a means of presenting information.

Another interesting finding is that the majority of female users (40%) are found in Cluster 5, whereas male users (43%) primarily emerge in Cluster 2 (see Table IV). Coinciding with computer experience, Table IV also depicts 43% of intermediate users as being female and 42% of expert users as males. In summary, females have shown to exhibit similar experience to intermediate computer users, whilst males exhibited comparable computer experience to expert users.

V. CONCLUSION

User interfaces, and more specifically multimedia user interfaces, aim to communicate information effectively to a wide range of system users. However, each individual differs in their demographics, skills and preferences and thus will prefer different interface features. The study attempted to find the relationships between human factors and users' preferences. For this purpose, the K-modes algorithm was applied to group users' preferences of multimedia interface features. Empirical results revealed a prominent division between diverse types of users across clusters. More specifically, gender differences and computer experience were shown to be primary causes for determining the engendered clusters and thus impact users' preferences. Therefore, the findings of this study can potentially be useful in developing personalized interactive multimedia learning systems that can accommodate the needs and preferences of different users.

Nonetheless, a small-scale study was conducted. Further work needs to be undertaken with a larger sample to provide additional evidence. Additional clustering techniques could be applied when analyzing users' preferences, such as hierarchical or fuzzy clustering, to investigate the quality and compactness of clusters.

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