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Exploring Technical Quality Factors That Enhance Mobile Learning Applications Services Using Data Mining Techniques

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ABSTRACT

Mobile learning (m-learning) has become an increasingly attractive solution for schools and universities that utilize new technologies in their teaching and learning setting. This study investigates the technical factors affecting the development of m-learning applications services from students' perspectives. It presents a model consisting of 12 technical factors, including content usefulness, scalability, security, functionality, accessibility, interface design, interactivity, reliability, availability, trust, responsiveness, and personalization. To evaluate the model, a questionnaire was designed and distributed to 151 students in Jerash University, Jordan. The results indicate that all technical factors have positive effects on learner satisfaction and overall m-learning applications service; however, the data mining analysis revealed that security and scalability factors exert a major impact on student satisfaction with m-learning applications services. This study gives insight for the future of developing and designing m-learning applications.

KEYWORDS

Data Mining Techniques, M-Learning, M-Learning Applications, M-Learning Deployment, M-Learning Implementation, Mobile Learning Application, Technical Factors, User Satisfaction

INTRODUCTION

In recent years, the rapid development in wireless and communication technologies and market forces have made mobile devices widespread and relatively cheap, with fast and easy internet access, mobility, and more convenience, including with regard to e-services such as e-commerce and educational applications such as mobile learning (m-learning) (Almaiah et al., 2016; Sarrab et al., 2015; Wu et al., 2012). M-learning is galvanizing technology utilization in higher education, enabling the delivery of learning materials anytime, anywhere, and providing a strong opportunity for students and lecturers to engage, communicate, collaborate, and share learning contents (Ali et al., 2012). Furthermore, using mobile technologies in learning environments can offer control over learning, portability in terms of time and place, and wide interaction (Jones et al., 2006; Traxler, 2009). The term 'm-learning' has come to encompass all of these attributes in a pedagogical context.

Technologies support learning and teaching are attracting many educators in different educational fields to provide more efficient learning and teaching methods (Virtanen et al., 2018). Many researchers investigated the benefits of m-learning for teaching and learning within schools and universities environments. M-learning has been utilized as a tool to support secondary school students learning basic programming concepts (Giannakoulas & Xinogalos, 2018), to improve students learning ability

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to discover new knowledge in learning natural science (Hung et al., 2014), learning resources in museums (wang et al., 2016), and learning contents and location information using active learning support system (ALESS) (Hsu et al., 2016). In addition, m-learning is an eminently suitable technology for application in conventional higher education course teaching. It supports collaborative learning, which is particularly useful in language learning as well as its general facilitation of ubiquitous learning services (Alnabhan et al., 2018; Huang et al., 2016; Troussas et al., 2014). It has been used to help undergraduate students learn computer programming (John & Rani, 2015), facilitate learning computing and mathematics courses (Drigas & Pappas, 2015; Oyelere & Suhonen, 2016), and help nursing students in their practical training (Guo et al., 2007; Wu et al., 2012).

M-learning users try to find applications that satisfy their requirements for learning services. In other words, they demand services of necessary quality that improve their satisfaction to use m-learning applications (Kim and Ong, 2005). The quality of m-learning services has been evaluated in terms of the overall performance that affects student learning (Benhamida et al., 2017). The principle idea in learning environments is that the quality of services and user satisfaction are the key factors of successful learning and teaching processes. Quality of service is assayed in terms of users' perceptions of how good m-learning applications are (Sarrab et al., 2016). Delone and Mclean (2003) indicate that system quality influences user satisfaction towards systems. Many researchers clarify that factors related to system quality play a significant role in successful system deployment (Almarashdeh et al., 2010).

There is a shortage of research considering the technical quality aspects of m-learning applications services in higher education institutes. there are a few studies that discuss this topic. The novelty of this study is to explore and evaluate technical quality factors that help the development of m-learning applications in higher education environments. This can provide high quality services which motivate students, instructors, and decision makers to use and implement m-learning technology. The study contributes to m-learning researches by adding comprehensible and clear model that contains technical quality factors that should be consider while design and implement m-learning applications in higher education.

RELATED RESEARCH

M-learning offers a good opportunity for learning and teaching process. Several studies have investigated the design of m-learning applications in terms of pedagogical or technical aspects and issues (Oyelere et al., 2018). M-learning systems providing great service quality and stakeholder satisfaction are considered the main factor for a successful m-learning process in higher education environments (Sarrab et al., 2016). Al-Mushasha and Hassan (2009) investigated university students' perceptions about m-learning services' quality, students' satisfaction with m-learning services, and students' behavioral intention to utilize m-learning in their studies. They proposed a service quality model for m-learning in university context that measured ten technical factors derived from service quality, information quality, and system quality on overall students' perceived services quality. In addition, they measured the relationship between overall perceived quality, learner satisfaction, and behavioral intention. The results indicated that the technical factors of interface design, trust, content usefulness, content adequacy, ease of use, reliability, accessibility, and interactivity support m-learning services for university students. Furthermore, the results indicated that there is a relationship between overall perceived m-learning services and student satisfaction, and between student satisfaction and behavioral intention to use m-learning.

Almaiah et al. (2016) investigated the factors that enhance mobile learning system quality based on university students' perspectives. They presented and tested three frameworks for m-learning system based on quality factors. The three frameworks depend on three types of quality factors with eleven sub-quality factors: (1) information quality, concerning content usefulness and adequacy; (2) system quality, concerning functionality, accessibility, interactivity, interface design, and ease of use;

and (3) service quality, including availability, personalization, trust, and responsiveness. The data were collected from a total 392 graduate and undergraduate students from five Jordanian universities. The results indicated that all quality factors supported high-quality of m-learning systems that meet student requirements and contribute to the successful deployment of m-learning system in higher educational institutes.

Sarrab et al. (2016) proposed and described a model that contains the technical aspects of mobile learning services quality. A group of technical quality factors was derived from mobile learning application previous studies, with concentration on mobile application software for learning and teaching. The model includes flexibility, scalability, usability, availability, quick response, maintainability, performance, functionality, reliability, connectivity, user interface, and security.

To validate the workability of the proposed model, the researchers examined the twelve components of the model (technical quality factors) with different and well-known mobile learning platforms empirically. Four case studies were investigated against the technical quality factors in order to determine which technical factor contributes to and enhances the development of m-learning application services in the education context. The case studies were the following m-learning systems: MOODEL, Blackboard, Schoology, and Edmodo. The results indicate that there are relationships between the overall technical aspects of the proposed model and learner satisfaction. In addition, the model supports the overall learning process by validating the technical aspects while control the quality of mobile learning deployed.

Other studies explored the factors that affect the continuous usage of m-learning service within higher education institutions. Glood et al. (2018) tested the effect of information quality, services quality, and compatibility on user satisfaction, and finally the continuous usage of m-learning. The findings indicated that information quality, services quality, and compatibility affect the usage of m-learning through user satisfaction. Furthermore, the findings suggest that m-learning service providers need to provide high quality information, good services, and compatibility to maintain the post adoption of m-learning services.

It is worth to mention that a lot of studies in m-learning field concentrate on m-learning acceptance using Technology acceptance model (TAM) (Liu et al., 2010) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Abu Al-Aish & Love, 2013; Venkatesh et al., 2003). The aim of these studies was to investigate user's behavioral attention toward use m-learning. Other studies aimed to build frameworks and models for m-learning system in education environment (Motiwalla, 2007) to discuss the benefit and challenged of m-learning. These models ignored the quality factors that could participate to successful use and implementation of m-learning in higher education institutes. However, there is a shortage of researches that considering the technical quality of m-learning application services. Therefore, this study aims to propose a model of technical quality factors that enhance m-learning application services, and to examine which of technical quality factors that have the most affect and contribute to the use and implementation of m-learning services in higher education environment. In addition, the data analysis in pervious researches utilized descriptive or multiple regression analysis to test the model designed or to evaluate the effectiveness of model factors through comparative studies with current m-learning platforms. The data analysis in this research utilize the data mining techniques that give more accurate results.

TECHNICAL QUALITY FACTORS

A model of technical quality factors was derived from literature review and developed based on software quality of m-learning applications (Almaiah et al., 2016; Al-Mushasha & Hassan, 2009; Sarrab et al., 2016). The model addresses the most common and theoretical technical aspects of m-learning application services, such as content usefulness, scalability, security, functionality, accessibility, interface design, interactivity, reliability, availability, rust, responsiveness, and personalization. Figure 1 illustrates the model.

Table (1) explains the related m-learning applications features for every technical factor and supporting references. These features are suggested from previous literature studies that explored mobile application software quality.

RESEARCH METHODOLOGY

This study utilized a quantitative questionnaire method to explore technical factors that enhance m-learning services. The questionnaire was designed from previous work to capture university students' feedback about the technical factor proposed in the model (Figure 1). The questionnaire contains questions about students' demographic information, and 33 items measuring 12 constructs.

The questionnaire was distributed to undergraduate students in the Faculty of Computer Science and Information Technology and the Faculty of Engineering, Jerash University. Students from different classes were invited to participate and complete the questionnaire in their class. A brief description about the study objectives and a definition of m-learning and its services were given by the researcher before students started answering the questionnaire. A total number of 151 responses were obtained. After the data were collected, a pre-processing of the data was conducting including data cleaning and data conversion. The next step was data set analysis using descriptive analysis and data mining techniques (simple K-means, expectation–maximization (EM), Apriori Association Algorithm and Multilayer Perceptron (MLP). finally, results representation. Figure 2 explain the object process diagram.

Figure 1. Proposed technical factors model

Table 1. Proposed model factors and related m-learning applications features

Technical factor	Related m-learning applications features	Reference
Content Usefulness	Up-to-date, accurate content, that fits users' needs, including multimedia and collaborative content.	Almaiah et al. (2016)
Scalability	Ability to accommodate and adapt changes made to the application, ability to handle multiple types of contents and large number of users.	Wingkvist (2009)
Security	Keeping data confidentially, with integrity and privacy. Implementing authentication and authorization.	Sarrab et al. (2016)
Functionality	Suitability, compliance, accuracy, interoperability, privacy, easy navigation.	Almaiah et al. (2016), Sarrab et al. (2016)
Accessibility	Ability to download files, upload files, easy access to learning materials and services using 3G, 4G, and Wi-Fi.	Almaiah et al. (2016)
Interface Design	Ease of use, attractive interface, user satisfaction, attractivity, learnability, user-friendly, consistency for different platforms.	Almaiah et al. (2016), Sarrab et al. (2016)
Interactivity	Sharing learning content with students and lecturers, discussing and collaborative learning among learning community.	Almaiah et al. (2016)
Reliability	Perform its function and operation without failure; high processing, performance, and accuracy; robustness, recoverability, and maturity.	Sarrab et al. (2016)
Availability	Provide learning content and services anytime, anywhere.	Almaiah et al. (2016)
Trust	Safe transaction, trust services, security features.	Al-Mushasha and Hassan (2009), Almaiah et al. (2016)
Responsiveness	Immediate response, assist users all the time, prompt services, reduce loading.	Almaiah et al. (2016), Sarrab et al. (2016)
Personalization	Control learning, personalized message, record performance.	Almaiah et al. (2016)

DATA ANALYSIS RESULTS

The data analysis method for this research consists of two steps. Step one was conducted using descriptive analysis to find the mean, standard deviation and reliability for all items using SPPS 16. Step two utilizing data mining techniques applied on WEKA.

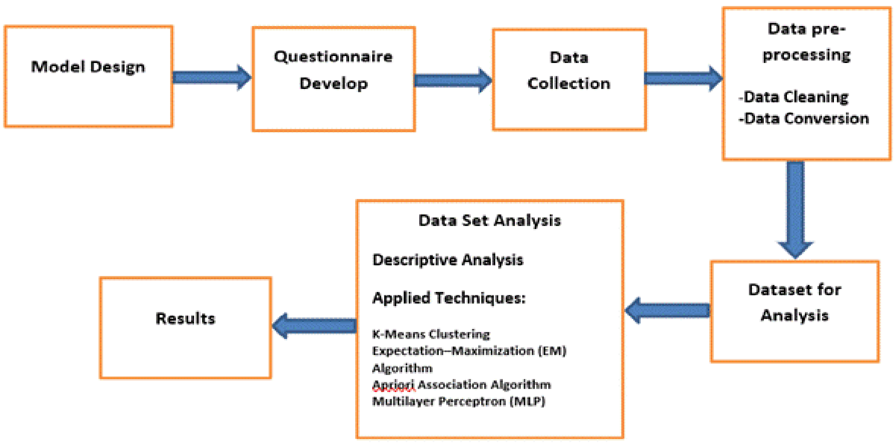
Descriptive Analysis

Table (2) represents participants' demographic data, including their gender, age, subject, kinds of mobile devices, and usability of m-learning. Table (3) shows the mean, standard deviation, and Cronbach's alpha for all attributes. Cronbach's alpha test was conducted to check the reliability of the measured data. The coefficients ranged between 0.70 and 0.80, indicating acceptability (De Vellis, 2003; Sekaran, 2003).

Applied Techniques

Step two of Data Analysis was performed using data mining techniques applied on WEKA. Three data mining techniques provided by WEKA were used to analyze the data, as they are most suitable for our case: clustering, classification and association Rules. Clustering algorithms are simple K-means and expectation–maximization (EM). The classification algorithm utilized multilayer perceptron (MLP) while the association rules generate a set of rules using the Apriori algorithm.

Figure 2. Object process diagram



Clustering is an unsupervised learning technique which provides the ability of grouping data in order to find the frequent patterns from our dataset. With clustering there are no class attributes in the data. Clustering thus helps us determining the class attributes from our dataset.

To compare the performance of the EM and K-means algorithms, our data were analyzed using the experimental clustering for all attributes. To compare the performance of K-means and EM, the same data were applied using the WEKA machine learning program.

Experimental Setup

This research conducted preliminary experiments to determine the suitable configuration of the classification and clustering methods for a proper data analysis. At first, it is implemented with its default parameter settings. Then, its parameter values are carefully tuned to obtain the desired results. Using Weka version 3.6, experiments are conducted on a Windows 10 machine with Core i5 processor and 4 GB of RAM. Table 4 shows the parameter settings for the K-means, EM, Apriori and MLP.

K-Means Clustering

The K-means clustering algorithm is effective, simple and easy to implement. Also, it is easy to interpret the clustering results. It can be considered as fast and efficient algorithm in terms of computational cost. Table 5 shows the outcomes of the simple K-means clustering algorithm applied to our dataset.

Based on Table 5, all the 151 items are clustered into 5 different clusters using a simple K-means clustering algorithm. The table tells us how each cluster comes together, with a “1” meaning everyone in that cluster shares the same value of one, and a “0” meaning everyone in that cluster has a value of zero for that attribute. Numbers are the average value of instances in the cluster. Each cluster shows us a type of preferences for the students, from which the following conclusions are drawn:

- Cluster 0 (18% of instances): this group comprises 23 year-old male Mathematics students using Samsung mobile devices. They mostly strongly agree with all services provided in m-learning, except they are neutral concerning the trust and availability of services.

Table 2. Participants' characteristics

Characteristic	Frequency	Percent	Cumulative percent
Gender			
Female	69	45.7	45.7
Male	82	54.3	100
Age			
19-21	56	37.1	37.1
22-25	78	51.6	88.7
Over 25	17	11.3	100
Subject			
CIS	18	11.9	11.9
Civil Engineering	17	11.3	23.2
CS	75	49.7	72.8
Math	9	6.0	78.8
Computer Network	32	21.2	100
Mobile device			
Huawei	66	43.7	43.7
iPhone	41	27.2	70.9
Nokia	2	1.3	72.2
Samsung	3	25.2	97.4
Sony	4	2.6	100
Use of m-learning			
Yes	144	95.4	95.4
No	7	4.6	100
Internet plan			
Yes	142	94.0	94.0
No	9	6.0	100
Years of using m-learning			
Less than 1 year	15	9.9	9.9
1-3 years	45	29.8	39.7
3-5 years	91	60.3	100

- Cluster 1 (32%): this group comprises 23 year-old female Computer Science students who use Huawei mobile devices. They mostly strongly agree with all services provided in m-learning.
- Cluster 2 (19%): this group comprises 21 year-old female students of Computer Science who use iPhone mobile devices. They mostly strongly agree with all services provided in m-learning.
- Cluster 3 (13%): this group is relatively small, and it is not statistically relevant nor significantly affecting the analysis, but it can be useful in supporting some factors (e.g. personalization and

Table 3. Mean, standard deviation, and Cronbach's alpha for all attributes

Factors	Items	Mean	Std Deviation	Cronbach's Alpha
	CU1	4.2583	0.82027	0.764
Contents Usefulness	CU2	4.4437	0.77140	
	CU3	4.4967	0.72915	
	CU4	4.3841	0.80714	
Scalability	SC1	4.2185	0.82376	0.701
	SC2	4.2649	0.85403	
Security	SE1	4.5364	0.75520	0.761
	SE2	4.5033	0.72915	
	SE3	4.3377	0.76496	
Functionality	FU1	4.2119	0.87643	0.721
	FU2	4.0331	0.90493	
	FU3	4.2318	0.83621	
Accessibility	ACC1	4.2848	0.85928	0.712
	ACC2	4.2450	0.75690	
	ACC3	4.3576	0.84336	
Interface Design	Inerface1	4.2517	0.73229	0.702
	Interface2	4.2781	0.74975	
	Interface3	4.4238	0.78687	
Interactivity	Interactivity1	4.2781	0.80960	0.726
	Iinteractivity2	4.3841	0.80714	
Reliability	RE1	4.4503	0.75444	0.713
	RE2	4.5033	0.68190	
Availability	AV1	4.2119	0.92815	0.710
	AV2	4.2384	0.87718	
Trust	TR1	4.3709	0.81335	0.755
	TR2	4.3510	0.74116	
	TR3	4.3311	0.82237	
Responsiveness	RESP1	4.3841	0.79884	0.723

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Table 3. Continued

Factors	Items	Mean	Std Deviation	Cronbach's Alpha
	RESP2	4.2781	0.76732	
	RESP3	4.3377	0.72927	
Personalization	PERS1	4.3311	0.78928	0.734
	PERS2	4.2583	0.84430	
	PERS3	4.3377	0.79906	

Table 4. Experimental setup for K-means, EM, Apriori and MLP

Algorithm	Parameter	Value
K-means	Distance function	Euclidean distance
	Initialization method	Random
	Number of clusters	5
	Seed number	10
	Cluster mode	percentage split 66%
EM	Initialization method	Random
	Number of clusters	5
	Seed number	100
	Cluster mode	10 folds cross-validation
Apriori	Delta=0.05	0.05
	Metric = confidence	Confidence
	Minimum metric	.9
	Number of rules	10
MLP	Hidden layers	number of attributes +number of classes
	Learning rate	.03
	Momentum	.02
	Epoch	100
	Test mode	percentage split 66%

responsiveness) considered by other groups. This group comprises 20 year-old male students of Computer Science who use Huawei mobile devices. They are mainly disappointed or neutral with the services provided by the m-learning.

- Cluster 4 (19%): this group comprises 27 year-old Male Computer Network students who use Samsung mobile devices. Even though they are 27 years old and used m-learning for less than a year, they are greatly satisfied with all services provided via m-learning and totally agree with it.

Expectation–Maximization (EM) Algorithm

Table 6 (Appendix 2) shows the results of EM clustering algorithm experimental applied to our dataset. Table 6 shows relatively similar results to the ones in Table 5, but with less quality. However, results obtained by the EM clustering algorithm are more detailed with respect to the mean errors of correct clustering. It provides the mean and standard deviations for each attribute value in each cluster.

Results obtained by K-means clustering algorithm used the same conditions as were set for the EM clustering algorithm. The results showed that the processing speed of the K-means clustering (0.01 seconds) is faster than that with the EM clustering (0.06 seconds). K-means performed 5 iterations, while the EM clustering performed 3. K-means showed a sum of squared errors within clusters about 47.8, while the EM showed a log likelihood of -30.19. Considering attributes values in the Tables (1) and (2), K-means showed the percentage of respondents who belonged to their cluster based on their answers (data types or scales), while the EM clustering showed the mean and standard deviation values for each attribute.

The classification accuracy of the data is 99% for the K-means, 100% accuracy was obtained by the EM. In order to simplify the results, Figure (2) visualizes the clusters obtained by the K-means clustering algorithm.

Taking one example from all instances, Using Mobile Learning versus Content Usefulness, it can be seen from Figure (3) that the 5 clusters are grouped for the values of the two attributes (namely: use m-learning as the X axis and CU1 as the Y axis), and are mainly concentrated at the top-left corner around the scale number 5. Which indicates a strongly agree of the provided service in mobile learning. In other words, most students are using mobile learning services due to their satisfaction with the content Usefulness. This represents the students' satisfaction with using m-learning frequently rather than occasionally. This is one example, the rest of the instances show a similar degree of satisfaction, such as: Scalability, Security, Interface Design, and Reliability.

Multilayer Perceptron (MLP)

The multilayer perceptron (MLP) is a class of feed forward artificial neural network (ANN) which uses a supervised learning technique called back propagation algorithm for training. MLP is utilized for classification tasks. It consists of three layers: input layer, hidden layer, and output layer. Learning is typically based on the minimization of measurement errors between network outputs and desired outputs.

Appling the MLP to our data sets, we found that scalability factor including SC1 and SC2 has a high accuracy of 99.33% (the highest accuracy rate in comparison with other factors). This result revealed that the scalability factor of m-learning application affects student satisfaction with m-learning application services. Table 6 shows the results obtained from multilayer perceptron algorithm.

Confusion Matrix

a	b	classified as
0	139	a=yes
11	1	b=no

Table 5. K-means clustering algorithm experimental results (final cluster centroids) *

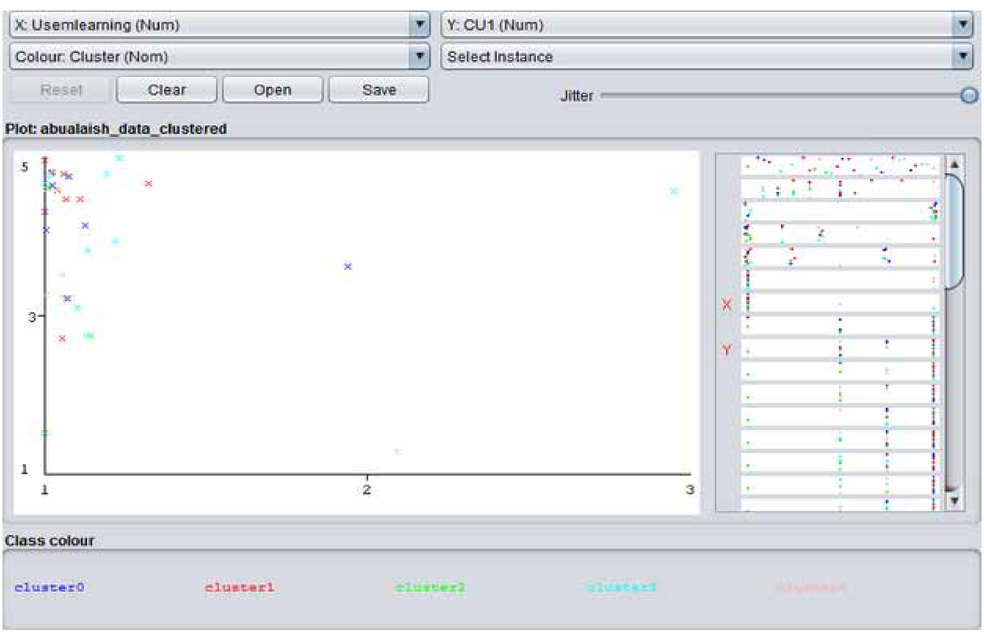
Initial starting points (random):						
Cluster				0:		
23,M,MATH,SAM,1,1,3,4,4,5,5,5,4,5,5,5,5,4,5,5,5,3,5,5,5,4,5,5,5,3,3,3,4,5,5,4,4,5,5,5						
Cluster				1:		
23,F,CS,HU,1,1,3,5,4,4,5,4,5,4,5,4,5,4,5,4,5,4,4,4,4,4,4,4,4,4,5,4,4,5,4,5,5,5,5,5						
Cluster				2:		
21,F,CS,IPHONE,1,1,2,5,5,5,5,4,5,5,5,5,4,4,4,4,3,5,5,4,4,4,5,5,5,5,5,5,4,5,5,5,4,5,5,5						
Cluster				3:		
20,M,CS,HU,1,2,1,5,3,4,3,4,2,4,3,3,3,3,4,2,3,4,5,3,3,3,5,3,4,2,3,2,3,3,2,4,5,4,3,5						
Cluster				4:		
27,M,NET,SAM,1,1,1,5,5,5,5,5,5,5,5,5,4,4,4,5,5,5,5,5,5,5,5,5,5,5,4,5,5,5,5,5,5,5,5,5						
Final Cluster Centroids:						
Cluster#						
Attribute	Full Data (151.0)	0 (27.0)	01 (49.0)	2 (28.0)	3 (19.0)	4 (28.0)
Age	22.8079	22.5185	22.7755	23.1071	22.3684	23.1429
Gender	M	M	F	F	M	M
Subject	CS	CS	CS	CS	CS	NET
Mobiledevice	HU	SAM	HI	IPHONE	HU	SAM
Internetplan	105.96	1.1111	1.0816	1	1.0526	1.0357
Usemlearning	1.1126	1.037	1.0816	1.0357	1.1579	1.2857
Yearsmlearning	2.5033	2.4444	2.6939	2.2857	2.0526	2.75
CU1	4.245	4.2593	4.4082	4.2857	3.2105	4.6071
CU2	4.4305	4.4444	4.5306	4.6786	3.4211	4.6786
CU3	4.4834	4.3704	4.5714	4.7143	3.4737	4.8929
CU4	4.3709	4.2222	4.5306	4.2857	3.4737	4.9286
SC1	4.2053	3.7778	4.4286	4.3214	3.2632	4.75
SC2	4.2517	3.8148	4.4896	4.5	3.4211	4.5714
SE1	4.5232	4.4074	4.4694	4.9286	3.5789	4.9643
SE2	4.4901	4.5185	4.6327	4.6701	3.3684	4.8571
SE3	4.3245	4.2963	4.449	4.4643	3.4211	4.6071
FU1	4.1987	4	4.3265	4.4286	3.0526	4.7143
FU2	4.0199	3.7037	4.3265	3.9286	3.0526	4.5357
FU3	4.2185	4.1481	4.3469	4.3929	2.8947	4.7857
ACC1	4.1854	4.2222	4.4286	4.5	3.1579	4.1071
ACC2	4.2119	3.963	4.4082	4.3571	3.4737	4.4643
ACC3	4.2781	3.8889	4.4286	4.6429	3.1579	4.7857
Interaface1	4.2384	4.1111	4.2041	4.5714	3.5263	4.5714
Interface2	4.2649	4.0741	4.3265	4.6071	3.3158	4.6429
Interface3	4.4106	4.5556	4.449	4.75	3.2105	4.6786

continued on next page

Table 5. Continued

Initial starting points (random):						
Interactivity1	4.2649	4.1111	4.3061	4.5714	3.3158	4.6786
Interactivity2	4.3709	4.4444	4.5102	4.4286	3.0526	4.8929
RE1	4.4371	4.2593	4.6735	4.75	3.0526	4.8214
RE2	4.4768	4.4815	4.4694	4.7143	3.4737	4.9286
AV1	4.2252	4.1852	4.3061	4.6071	3.2105	4.4286
AV2	4.2384	3.8519	4.449	4.5357	3.2632	4.6071
TR1	4.3709	4.1481	4.551	4.6071	3.0526	4.9286
TR2	4.3377	4.1481	4.5306	4.4286	3.4211	4.7143
TR3	4.3311	4.1111	4.5714	4.4643	3.2105	4.75
RESP1	4.3841	4.2963	4.5714	4.4643	3.2632	4.8214
RESP2	4.2781	3.9259	4.3878	4.5	3.5263	4.7143
RESP3	4.3377	4.037	4.2857	4.5714	3.7895	4.8571
PERS1	4.3311	4	4.551	4.4286	3.4737	4.75
PERS2	4.2583	4.0741	4.4898	4.25	3.3684	4.6429
PERS3	4.3377	3.963	4.4694	4.5	3.7368	4.7143
Cluttered Instances						
0	27 (18%)					
1	49 (32%)					
2	28 (19%)					
3	19 (13%)					
4	28 (19%)					

Figure 3. A visualization of results obtained by the K-means clustering algorithm for 2 instances



Apriori Association Algorithm

The Apriori association algorithm is implemented for a more detailed relationship between instances. For example, it identifies the instances (services) that affect student satisfaction with mobile learning. Three sets of rules are produced, with a minimum support of 55% of the instances, and confidence greater than 90%. These rulesets are 15 items, 18 items, and 3 items.

The best rules found are:

1. Interface3=5 88 ==> Use m-learning=1 87 <conf:(0.99)> lift:(1.07) lev:(0.04) [5] conv:(3.5)
2. Use m-learning=1 SE1=5 96 ==> internet plan=1 94 <conf:(0.98)> lift:(1.04) lev:(0.02) [3] conv:(1.91)
3. Use ml earning=1 SE2=5 91 ==> internet plan=1 89 <conf:(0.98)> lift:(1.04) lev:(0.02) [3] conv:(1.81)
4. SE1=5 102 ==> internet plan=1 99 <conf:(0.97)> lift:(1.03) lev:(0.02) [3] conv:(1.52)
5. SE2=5 95 ==> internet plan=1 92 <conf:(0.97)> lift:(1.03) lev:(0.02) [2] conv:(1.42)
6. internet plan=1 SE2=5 92 ==> Use m-learning=1 89 <conf:(0.97)> lift:(1.05) lev:(0.03) [4] conv:(1.83)
7. SE2=5 95 ==> Use m-learning=1 91 <conf:(0.96)> lift:(1.04) lev:(0.02) [3] conv:(1.51)
8. CU2=5 89 ==> Use m-learning=1 85 <conf:(0.96)> lift:(1.04) lev:(0.02) [3] conv:(1.41)
9. Use m-learning=1 139 ==> internet plan=1 132 <conf:(0.95)> lift:(1.01) lev:(0.01) [1] conv:(1.04)
10. internet plan=1 SE1=5 99 ==> Use m-learning=1 94 <conf:(0.95)> lift:(1.03) lev:(0.02) [2] conv:(1.31)

It can be seen that, for example rule number 10, 94 students are willing to use m-learning if they have an internet plan and are totally satisfied with the security service. The factor Use m-learning showed a significant level of importance for 139 students in rule number 9. In nine rules, using mobile learning (Use m-learning) is totally dependent on the Security service, and in one rule the Content Quality plays a role in using mobile learning. It is worth mentioning that the security factor has been heavily considered by students (95 strongly agreed students), which is presented in rules number 4, 5, and 7 as a major independent factor, especially the SE2 factor (privacy and confidentiality), which appeared in 2 rules with a high confidence of 97%. SE1 and SE2 factors were presented in rules 2, 3, 6, and 10 as dependent factors upon the internet plan and Use m-learning factors. In addition, the factor SE1 factor appearing in rule number 4 has the majority of students (102 students out of 151) preferring secure credentials over others. Overall, it can be concluded that the factors SE1 and SE2 have the greatest impact on satisfying students' needs in using m-learning (Use m-learning).

DISCUSSION

This study has presented a data mining technique to investigate the quality factors of m-learning applications services that support learning and teaching in higher education institutes. The researcher proposed a quality factors model that aims to blending all technical aspects of m-learning services that might affect student's satisfaction with m-learning services. The first part of data analysis was conducted using descriptive statistics. The results revealed that all factors suggested by the proposed model have positive affect on student's satisfaction with m-learning applications services. Table 3

Table 6. Multilayer perceptron algorithms results

Detailed Accuracy by class								
Weighted Avg	TP Rate	FP Rate	Precision	Recall	F-measure	MCC	Roc Area	PRC
	0.992	0.954	0.954	0.991	1.000	0.993	0.083	1.000
	0.926	0.943	0.954	0.957	0.917	1.000	0.000	0.917
	0.987	0.943	0.954	0.993	0.993	0.993	0.077	0.993

shows that all questionnaire items have a mean ranged between 4.03 and 4.53 which falls between 'agree' and 'strongly agree' and indicated that the participants had agreed thoughts regarding to the model factors. This result similar with results obtained by previous researches (Almaiah et al. (2016); Sarrab et al. (2106)).

The second part of data analysis was conducted using data mining techniques applied on WEKA. In first step the researcher performed analysis with two clustering techniques/algorithms, namely k-mean and EM (Dey et al., 2019) in order to identify groups of items that may have a significant impact on the satisfaction of students in using or relying on mobile technology as an assistant tool for learning. Both algorithms indicated the importance of the "*Security*" factor as a critical component in designing a successful / preferred m-learning application. Both algorithms were implemented to support each other in their indication of some factor of interest. Upon our preliminary experiments, one clustering algorithm was not enough to determine a significant factor (e.g. K-means) with 99% accuracy. Therefore, another clustering algorithm (e.g. EM) was implemented to support the grouping generated by k-means. It is clearly that EM has obtained a higher accuracy (100%) than the K-means. Hence, proceeding with the generated grouping (security factor) to the next data mining technique.

Then, the second step, a classification algorithm (namely, MLP) was implemented to predict a descriptive model of the grouping generated by the clustering algorithms in first step. However, this classification step has further indicated the significance of the "*scalability*" factor with a high F-measure (0.91) and a high (0.99) model accuracy. So, two significant factors are now considered for the third step. In the third step, the association rules algorithm (Apriori) was employed to predict a set of rules driven from the classification or rather the description (generated in step two) of the grouped factors from step one. Apriori has generated 10 sequences of rules that again support the significance of the "*security*" factor. Consecutively, these 3 steps recommended potential design components for learners based on the predefined factors. The employed algorithms in this proposed model are not to compete for accuracy; they are employed sequentially in order to come out with the best recommendation.

Since it is well known that data mining techniques are capable of discovering patterns and groups of potential data, such as students/learners' preferences or design factors that impact a successful development of m-learning applications. This study highlights model for applying data mining in m-learning to determine its potential.

Based on that, it is required to link learners' preferences and the design components of a preferable development of m-learning applications. Hence, using data mining views a multidimensional perspective. This might lead to a better decision such as, what is the best configuration of designing a successful m-learning application, what are the critical components/requirements that hinder/support the success of m-learning applications, or even that hinder/support learners interacting effectively with the application. In general, data mining techniques are to discover patterns/factors that have the potential to become an actual application.

The research results focusing on security and scalability factors because they have highest impact on student's satisfaction with m-learning services. Students need m-learning applications that keep user's data confidentially and privacy. Also, has ability to accommodate changes made to the application and ability to handle multiple types of contents and large number of users (Sarrab et al., 2016). In addition, the factors that suggestions by the proposed model will enhance the implementation of mobile learning through improving learning performance and learning contexts (Garcia-Cabot et al., 2015).

Contribution and Benefit of Research Outcomes

There is a lake of researches that investigated the technical aspects of m-learning applications services. This research added value to the previous literature in mobile learning applications services through designing a model of technical quality factors that enhanced this technology in universities teaching and learning methods. The results indicate that students consider security and scalability are the most important services that should m-learning applications provide. This result gives an important insight for people who designing and developing m-learning applications.

Security should be considered while designing m-learning applications; m-learning applications have to protect data and implement control over authentication, authorization and sharing contents. Students worried about losing confidential information, stop having privacy, change of learning quality and authorized users' access learning contents. Lecturers also concerned about control over e-examinations. Therefore m-learning designers should integrate some security technologies in m-learning applications. This includes access control mechanisms, firewalls, anti-viruses, digital identity to each users, authentication and authorization.

Furthermore, scalability is other factor that needs to be integrated with m-learning applications. M-learning applications should have ability to handle and manage a large number of data and allowed a large number of users to access applications from different locations at the same time. M-learning applications need to be refined and extended in order to outfit different needs and complex issues. In addition, m-learning applications should have a suitable graphical user interface that can be modified to integrate newly features.

CONCLUSION

Overall, the results of this research reveal that all of the quality factors have a positive effect on student satisfaction with m-learning application services. Furthermore, these factors meet students' needs and requirements to implement this tool within the learning process. Security and scalability factors were discovered to be a quality aspect that has the highest impact on student satisfaction with m-learning application services. The classification accuracy of the data is 99% for the K-means, while 100% accuracy was obtained by the EM for the "security" factor, and 99.33% accuracy was achieved by the MLP for the "scalability" factor.

This research provides empirical support for discovering the guidelines and instructions to design and develop high-quality m-learning applications. Designers should consider all technical factors in the proposed model with more attention to security and scalability factors while designing and developing m-learning applications.

This study is limited to university students more researches for universities lecturers are highly needed to evaluate the model proposed. Also, there is a difficulty to compare the study results with similar research due to the lake of researches in technical aspect of m-learning quality services that utilized same data mining techniques. Furthermore, the data analysis of this study limited to some technical data mining algorithms, Next researches should use other algorithms with high performance. Future work might aim to investigate the feasibility of model components on different mobile learning applications, and additional work is needed to integrate more nontechnical factors in the model, including teaching pedagogy, learning approach, and management support.

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APPENDIX 1: QUESTIONNAIRE

Age: Gender: Subject and level:

1. What kind of mobile device you have: ....
2. Do you have a mobile internet package plan? 1. Yes 2. No
   Explain your connection type and speed……………………………………………..
3. Do you use m-learning in your studies? 1. Yes 2. No
4. Years of using m-learning
   1. less than 1 year 2. 1-3 years 3. 3-5 years

On a scale of 1 to 5, indicate with an û how strongly you agree or disagree with each of the following statements.

Rating Scale

1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree

		1	2	3	4	5
Content quality						
CU1	It is important for m-learning applications to provide will-aimed content.					
CU2	It is important for m-learning applications to provide text, audio and video content					
CU3	It is important for m-learning applications to provide up-to-date content.					
CU4	It is important for m-learning applications to provide content that meets learners' needs.					
Scalability						
SC1	It important for m-learning applications to handle multiple types of content with a large amount of information and features.					
SC2	M-learning applications should handle the increasing number of users who want to access the application at the same time.					
Security						
SE1	M-learning applications should secure learners' username and password across its servers.					
SE2	It is important for m-learning applications to maintain the privacy and confidentiality of data stored and transferred for educational process.					
SE3	Recent security technologies that protect learners' information, access, and communication should be integrated with m-learning applications.					
Functionality						
FU1	It is important for m-learning applications to be compatible with different platforms (Android, IOS).					
FU2	M-learning applications should have a search engine that facilitates searching for specific functions.					
FU3	M-learning application interfaces should provide a good size and resolution.					
Accessibility						
ACC1	M-learning applications should offer the ability to up-load and download attachment files.					
ACC2	M-learning applications should allow students and lecturers to access and submit learning content in multiple formats.					
ACC3	M-learning applications should allow accessing learning materials and services by using 3G,4G, WiFi, and offline					
Interface design						

continued on next page

Rating Scale Continued

		1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
Inerface1	It is important for m-learning applications to provide attractive interface, including graphics, animation, and colors).					
Interface2	It is important for m-learning applications to provide good icons and menu designs.					
Interface3	It is important for m-learning applications to provide good page layout.					
Interactivity (IN)						
Interactivity1	M-learning applications should allow learners to interact with their colleges and instructors via online messages.					
Ineractivity2	M-learning applications should make it easy to share and exchange learning contents among the learning community					
Reliability						
RE1	M-learning applications should be reliable, with high performance and accuracy, battery life, and processing power.					
RE2	It is important for m-learning applications to overcome issues like software fault and crash frequency.					
Availability						
AV1	M-learning applications should provide learning materials and services anywhere					
AV2	M-learning applications should provide learning materials and services anytime.					
Trust						
TR1	M-learning applications should provide safe and trustworthy transactions.					
TR2	M-learning applications should keep students' personal data in confidence.					
TR3	M-learning applications should provide secure features.					
Responsiveness						
RESP1	It is important for m-learning applications to provide learners with quick services					
RESP2	M-learning applications need to assist learners all the time they use it.					
RESP3	M-learning applications have to provide learners with feedback that responds to their needs.					
Personalization						
PERS1	It is important for m-learning applications to enable learners to choose how they want to learn.					
PERS2	It is important for m-learning applications to allow learners to learn the content they prefer.					
PERS3	It is important for m-learning applications to enable learners to control their learning process.					

APPENDIX 2:

Table 7. EM clustering algorithm experimental results

Cluster					
Attribute	0	1	2	3	4
	(0.23)	(0.23)	(0.3)	(0.12)	(0.11)
Age					
Mean	23.3776	24.1333	21.2532	22.6569	23.2455
Std. dev.	2.9625	2.9875	1.4057	2.8198	0.9899
Gender					
F	21.2116	11	32.1599	6.0039	3.6246
M	15.6321	26.1067	15.4194	14.7415	15.1003
[total]	36.8436	37.1068	47.5793	20.7454	18.7249
subject					
CS	21.3041	17.1068	19.1749	10.0032	12.411
CIVIL	2.0575	9	5.0963	2.6183	3.228
NET	11.5732	7	10.4685	6.9073	1.051
CIS	1.9304	6	9.8255	3.2167	2.0274
MATH	2.9784	1	6.014	1	3.0075
[total]	39.8436	40.1068	50.5793	23.7454	21.7249
Mobile device					
HU	6.9478	17.1067	32.2439	12.7426	1.959
SAM	9.941	10	8.3061	2.0002	12.7526
SONY	2.9968	1	2.9904	1	1.0128
IPHONE	18.9581	10	6.0387	7.0026	4.0005
NOKIA	1	2	1.0001	1	1.9999
[total]	39.8436	40.1068	50.5793	23.7454	21.7249
Internet plan					
Mean	1.0861	1.2279	1.0552	1.155	1.0347
Std. dev.	0.0406	0	0.3308	0.2247	0.3408
Use mlearning					
mean	1.0861	1.2279	1.0552	1.155	1.0347
Std. dev.	0.2805	0.6355	0.2887	0.3619	0.2607
Years mlearning					
Mean	2.3761	2.9115	2.3461	2.0647	2.8314
Std. dev.	0.7245	0.284	0.6657	0.7709	0.3744
CU1					
Mean	4.4957	4.7091	4.036	3.163	4.5313
Std. dev.	0.5494	0.5712	0.7577	1.0582	0.586
CU2					
Mean	4.678	4.7721	4.2754	3.5529	4.6038

continued on next page

Table 7. Continued

Cluster					
Std. dev.	0.5243	0.5384	0.7424	1.2194	0.4891
CU3					
mean	4.6571	4.94	4.3611	3.511	4.5867
Std. dev.	0.4749	0.2375	0.7907	0.9896	0.602
CU4					
Mean	4.4862	4.943	4.0722	3.4132	4.8168
Std. dev.	0.7328	0.2318	0.7703	1.0469	0.3869
SC1					
Mean	4.3934	4.7691	3.9741	3.2315	4.3515
Std. dev.	0.6453	0.4214	0.8291	0.9736	0.6842
SC2					
Mean	4.5898	4.6012	4.2079	3.4882	3.7886
Std. dev.	0.4988	0.5947	0.9463	1.031	0.9061
SE1					
mean	4.6164	5	4.4766	3.6064	4.4825
Std. dev.	0.643	0.7986	0.743	1.1713	0.6098
SE2					
Mean	4.5414	4.9145	4.63	3.4462	4.2808
Std. dev.	0.6483	0.2796	0.4828	1.1285	0.749
SE3					
Mean	4.5902	4.6582	4.1734	3.4463	4.4665
Std. dev.	0.6433	0.6292	0.6712	0.9765	0.6988
FU1					
Mean	4.5145	4.9145	3.8435	2.8516	4.5158
Std. dev.	0.5547	0.2796	0.8204	0.7593	0.6077
FU2					
Mean	4.1888	4.6297	3.9066	2.7489	4.1212
Std. dev.	0.9214	0.5892	0.7103	0.9048	0.5862
FU3					
Mean	4.2287	5	4.0823	3.0613	4.2254
Std. dev.	0.5902	0.0004	0.645	1.1391	0.8101
ACC1					
Mean	4.4547	4.5412	4.1107	3.2136	4.1706
Std. dev.	1.0279	1.0502	0.8183	0.9565	0.8704
ACC2					
Mean	4.4584	4.6297	4.0668	3.2938	4.246
Std. dev.	0.6025	0.795	0.7479	0.8369	0.5321
ACC3					
mean	4.7677	5	4.0033	3.295	3.594

continued on next page

Table 7. Continued

Cluster					
Std. dev.	0.4224	0.9741	1.0219	0.9773	0.9334
Interface1					
Mean	4.5691	4.5982	4.0023	3.3686	4.4127
Std. dev.	0.4955	0.4903	0.7	1.0423	0.4974
Interface2					
Mean	4.5723	4.7436	3.9995	3.455	4.2505
Std. dev.	0.4947	0.4976	0.7237	0.9975	0.6382
Interface3					
Mean	4.7105	4.8006	4.2966	3.3394	4.4783
Std. dev.	0.4542	0.4654	0.7478	1.165	0.6073
Interactivity1					
mean	4.4741	4.7976	4.0838	3.3978	4.1763
Std. dev.	0.6152	0.4018	0.8507	1.0259	0.7183
Interactivity2					
Mean	4.4805	5	4.3159	3.1844	4.3014
Std. dev.	0.6921	0	0.6626	1.1329	0.5762
RE1					
mean	4.7679	4.8006	4.4289	3.0447	4.5676
Std. dev.	0.4222	0.4654	0.6584	0.6852	0.6782
RE2					
Mean	4.766	4.883	4.3409	3.5466	4.4346
Std. dev.	0.4233	0.3214	0.6615	0.9769	0.6987
AV1					
mean	4.5137	4.7721	4.1133	3.1933	3.9375
Std. dev.	0.5036	0.7581	0.8903	0.7634	1.0072
AV2					
Mean	4.6819	4.8006	4.0199	3.1805	3.9157
Std. dev.	0.4658	0.523	0.8992	0.6537	0.7942
TR1					
Mean	4.5994	4.997	4.3496	3.1376	4.0207
Std. dev.	0.49	0.055	0.6684	0.977	0.6156
TR2					
Mean	4.5138	4.8291	4.2904	3.3752	4.1476
Std. dev.	0.6038	0.5056	0.6031	0.9856	0.6775
TR3					
mean	4.6103	4.9145	4.1572	3.2465	4.2145
Std. dev.	0.5344	0.2796	0.7849	0.7826	0.8061
RESP1					
Mean	4.5831	4.997	4.1943	3.4461	4.2515
Std. dev.	0.5341	0.0551	0.7273	1.0296	0.8713

continued on next page

Table 7. Continued

Cluster					
RESP2					
Mean	4.3224	4.8291	4.089	3.3472	4.5885
Std. dev.	0.6193	0.3764	0.7288	0.7827	0.4932
RESP3					
Mean	4.2957	4.9115	4.1092	3.6379	4.6282
Std. dev.	0.6067	0.284	0.7383	0.6837	0.595
PERS1					
Mean	4.2688	4.943	4.1939	3.2938	4.7131
Std. dev.	0.6369	0.2318	0.6968	0.8983	0.4523
PERS2					
Mean	4.1885	4.8006	4.2886	3.3813	4.1653
Std. dev.	0.8405	0.3995	0.7551	0.9141	0.7715
PERS3					
Mean	4.2433	4.883	4.371	3.6598	4.0592
Std. dev.	0.5349	0.3214	0.6487	1.1185	1.0612
Clustered Instances					
0	32 (21%)				
1	39 (26%)				
2	46 (30%)				
3	19 (13%)				
4	15 (10%)				
Log likelihood: -30.19463					

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