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Mobile learning application usability: A pattern mining approach

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Abstract

User satisfaction is very important for mobile learning applications to provide the maximum academic outcome. Hence evaluating mobile learning systems is important to test their usability. Most of the previous studies used statistical approaches to test the usability of learning systems. The main objective of this study is to evaluate the usability of the mobile learning system using a data science approach. To evaluate the proposed mobile learning system, responses for a questionnaire were obtained from 100 system users After applying several preprocessing steps, the responses were evaluated using two pattern mining algorithms: Apriori and FP-Growth. According to the results, the Apriori algorithm shows 94% system usability while the FP-Growth algorithm ensures 93% system usability. It confirms the proposed mobile learning system's usability. Furthermore, it was observed that this pattern mining-based approach can be successfully applied in usability evaluation for learning systems.

Keywords: M-learning apps, M-Learning, Pattern mining, System evaluation, Usability

Introduction

Mobile learning (ML) can be defined as a learning mechanism that uses diverse learning contexts with social collaborations and interactions through personalized handheld equipment such as smartphones, tab devices, other portable mobile devices comprise computing capabilities. Further, it offers academic services free from time, place, and supports on-the-go learning and context-aware learning (Grant, 2019). ML provides better options for learners with busy lifestyles. Further, it provides learners, a secure learning environment in pandemic situations restricting them to an isolated atmosphere. However, for successful ML, various conditions needs to be satisfied, such as quality of the content, technology awareness, devices capable of learning, secure learning environment (Nagahawatta, Warren, & Yeoh, 2020), robust and reasonable connecting facilities, adequate and satisfactory mobile applications for learning, etc. The usability of a mobile application decides whether it supports adequate and satisfactory learning services to stakeholders. Therefore, usability evaluation is important for any learning system to get maximum yield from it.

System usability

The best usability evaluation factors in previous researches related to usability evaluation are efficiency, effectiveness, learnability, and user satisfaction. Further, it reveals that most usability evaluations are done with the system implementation (Mkpojiogu, Hussain, & Hassan, 2018). In another study, a systematic literature review on the usability of ML applications identified that the highest priority usability attribute is learnability while user satisfaction, usefulness, and ease of use are the next important usability attributes with equal significance. Lab-based quantitative and qualitative research methodologies were selected in the most number of researches (Kumar & Mohite, 2018). In previous studies, usability evaluation of e-learning and learning management system (LMS) can be found. An e-learning system designed to meet someone's requirements was tested for usability using 62 computer science students with a four-dimensional usability questionnaire consists usefulness, ease of use, ease of learning, and satisfaction. The evaluation confirmed the usability of the system in every dimension is satisfactory. Further, it reveals that the usefulness, ease of use, and ease of learning equally impact learner's gratification about the system (Hariyanto, Triyono, & Köhler, 2020). In another study, the user experience-based automated metrics were proposed to assess the e-Learning system usability for educators to utilize the automated systems in academic institutions with satisfaction (Harrati, Bouchrika, Tari, & Ladjailia, 2016). A study was conducted to evaluate the accessibility and usability of the instance of a popular institutional LMS. Questionnaire-based evaluation focus on interface, navigations, and easy-to-use facilities of the system. The study guaranteed the usability of the system while it recommended enhancing the system to adhere to educator requirements for pursuing academic services (Alturki, Aldraiweesh, & Kinshuck, 2016). On the other hand, various usability assessment guidelines and frameworks can be found in previous studies. Prevailing usability issues were identified using the previous usability guidelines. New solutions for those gaps are forwarded by introducing novel usability guidelines. The methods to apply these guidelines to mobile learning applications (MLA)s are also proposed. The quantitative evaluation techniques reveal the 81% confirmation by the participant for success in usability improvement in MLAs with proposed guidelines (Hujainah, et al., 2016). Usability evaluation of MLAs while conducting agile software development methodology is proposed. The evaluation recommends this approach as best suitable for experienced developers to conduct usability assessments in MLAs than field studies (Hussain, Saleh, Taher, Ahmed, & Lammasha, 2015). Research is carried out to evaluate the usability of MLA with 105 academic users. A quantitative survey reveals no question of the academic transactions and navigation of the app, but attractiveness is required to improve (Kuhnel, Seiler, Honal, & Ifenthaler, 2018). Augmented reality and gamification features integrated MLA in an outdoor learning environment was tested for usability. 70 students participated in the evaluation while quantitative and qualitative statistical analysis techniques were employed with system usability scales in the study. Students show eagerness to use the system with more than 70 percent system usability (Pombo & Marques, 2018).

Objectives of the study

The main objective of this study is to evaluate the mobile learning system (MLS) for usability. According to the literature, most studies use quantitative and qualitative based statistical analysis to evaluate the usability of learning systems. There is no evidence of using machine learning-based data mining approaches to evaluate usability in MLSs. To address this research gap authors proposed a pattern mining-based approach for evaluating the usability of the MLS.

Methodology/materials and methods

Mobile learning application

In this study, we evaluate the usability of the mobile MLA which is developed to utilize ML in Sri Lankan higher education. MLA is developed by customizing the Moodle mobile application (MMA). MMA is a platform-specific native app that has separate versions for android and iOS operating systems. Cordova/PhoneGap mobile application development framework with HTML, PHP, JavaScript, and ionic technologies are used to develop the MMA. Functionalities such as content upload, content creation, chat, notes, forum, quizzes, etc. are implemented using plugins (Dougiamas, 2021) and in this study, authors develop new plugins to implement new functionalities in the Moodle ML environment such as Annotate PDF, Checklist, Hot Question, and Game (Dolawattha, Pramadasa, & Jayaweera, 2019).

System usability scale (SUS)

System usability is done using various methods such as questionnaires, expert evaluation, and automated systems. SUS questionnaires are the extensively used method to examine the usability of a system. In this study positive version of the standard SUS with 5 points Likert scale was used (Lewis, 2018).

Table 1. *The system usability scale positive version*

Que. No	Question
01	I think that I would like to use the mobile application (MA) frequently
02	I found the MA to be simple
03	I thought the MA easy to use
04	I think that I could use the MA without the support of a technical person
05	I found the various functions in the MA were well-integrated
06	I thought there was a lot of consistency in the MA
07	I would imagine that most people would learn to use the MA very quickly
08	I found the MA very intuitive
09	I felt very confident using the MA
10	I could use the MA without having to learn anything new

Pattern mining algorithms

In this study authors used two popular pattern mining algorithms to evaluate the usability of MLS.

Apriori Algorithm: Latin term “Apriori” means “from what comes before”. In this algorithm, Bottom-up and breadth-first search strategies are considered. Agarwal and Srikant (1994) coined the Apriori algorithm based on frequent pattern mining for generating associate rules. Min_supp, Min_conf, Frequent itemsets, Apriori Property, Join Operation, Join Step, and Prune Step are the main terms associate with the Apriori algorithm (Suresh & Ramanjaneyulu, 2013).

Frequent Pattern (FP) Growth Algorithm: Another most prevailing pattern mining algorithm used in data mining and FP-tree is used to store frequent patterns. Calculating each database item's support count by scanning, deleting irregular patterns, and order remains are the main steps in this algorithm. Then frequent patterns are generated using FP-tree (Pei & Han, 2000). The efficiency of the algorithm is high as it scans the database only twice. It doesn't generate a candidate set and not suitable for mining patterns in online databases (Nasreen, Azam, Shehzad, Naeem, & Ghazanfar, 2014).

Definition for support threshold in pattern mining: The support of an itemset I is defined as the fraction of the transactions in the database $T=\{T_1, \ldots, T_n\}$ that contain I as a subset (Pei & Han, 2000).

Methodology

In this study, 100 learners study in the faculty of Social Sciences were participated. First, they were allowed to do academic activities such as access academic content, take quizzes, submit assignments, access forums, access chatting, and collaborative learning. Finally, they were asked to respond to the usability questionnaire. The questionnaire responses are based on the 5 points Likert scale. Likert scale values are 1 for strongly disagree, 2 for disagree, 3 for neutral, 4 for agree, and 5 for strongly agree. Then few preprocessing steps were done on questionnaire responses and converted to a dataset suitable for mining patterns and discover the information about the system usability. When creating the dataset, each question (Q1 to Q10) can be taken as an attribute in each transaction whose response Likert scale value greater than or equal to 4. Therefore, dataset items are the question numbers whose response value is equal to 4 or 5 (see Figure 1). Finally, the dataset was evaluated for the usability of the MLA with Apriori and FP-Growth algorithms.

SNo	Ans. Q1	Ans. Q2	Ans. Q3	Ans. Q4	Ans. Q5	Ans. Q6	Ans. Q7	Ans. Q8	Ans. Q9	Ans. Q10
01	3	2	4	4	5	3	2	5	5	5
02	4	5	4	5	5	4	5	2	2	5
03	4	3	4	4	4	4	5	2	5	5
...	...	...	...	...	...	...	...	...	...	...
100	4	5	3	4	5	4	4	3	4	5

Transaction	Items
T1	Q3, Q4, Q5, Q8, Q9, Q10
T2	Q1, Q2, Q3, Q4, Q5, Q6, Q7, Q10
T3	Q1, Q3, Q4, Q5, Q6, Q7, Q9, Q10
...	....
T100	Q1, Q2, Q4, Q5, Q6, Q7, Q9, Q10

Figure 1. *Dataset creation from questionnaire responses*

Results and Discussion

Results of Apriori algorithm: The Apriori algorithm was implemented using Python language and web-based Jupiter notebook environment. In this study, the Apriori model was built using the parameters such as min_support=0.5, min_confidence=0.0, min_lift=0.0 to control the association rules. These parameters were selected to have the popularity of a itemset is atleast 50%. Under these conditions, 175 association rules were generated and 12 best rules were selected for describing the usability of the MLA. When selecting these rules, items sets with maximum number of attributes were considered. Also authors limited the itemset with atleaset 5 items to represent atleast harlf attributes of a user response marked as 'agree' or 'strongly agree'.

***Table 2**. Apriori algorithm results*

Rule No	Item set	Support
150	'Q1', 'Q4', 'Q5', 'Q6', 'Q7',	90%
154	'Q1', 'Q5', 'Q6', 'Q7', 'Q9',	87%
155	'Q4', 'Q5', 'Q6', 'Q7', 'Q10',	53%
163	'Q3', 'Q4', 'Q5', 'Q7', 'Q9',	51%
165	'Q3', 'Q5', 'Q6', 'Q7', 'Q9',	50%
166	'Q4', 'Q5', 'Q6', 'Q7', 'Q9',	94%
167	'Q1', 'Q3', 'Q4', 'Q5', 'Q6', 'Q7',	53%
171	'Q1', 'Q3', 'Q5', 'Q6', 'Q7', 'Q9',	50%
172	'Q1', 'Q4', 'Q5', 'Q6', 'Q7', 'Q9',	87%
173	'Q4', 'Q5', 'Q6', 'Q7', 'Q9', 'Q10',	50%
174	'Q3', 'Q4', 'Q5', 'Q6', 'Q7', 'Q9',	50%
175	'Q1', 'Q3', 'Q4', 'Q5', 'Q6' ,'Q7', 'Q9',	50%

According to the above results, rule no 175 ensures 50% learner-responses marked as ‘Agree’ or ‘Strongly agree’ for 7 out of 10 usability questions in the questionnaire. Also, rule no 172 secures 87% learner-responses marked as ‘Agree’ or ‘Strongly Agree’ for 6 out of 10 questions in the questionnaire. Rule no 166 secures 94% learner-responses marked as ‘Agree’ or ‘Strongly Agree’ for 5 out of 10 questions in the questionnaire. Therefore, as per the definition of support threshold in pattern mining, the most number of respondents responded to the questionnaire as at least ‘Agree’. Hence according to the Apriori algorithm, it can be predicted that the proposed MLA is useable.

Results of FP-Growth algorithm: The FP-Growth algorithm implemented using the same technologies and environment with the dataset. Three types of best patterns were selected using the results of FP-Growth algorithm implementation.

***Table 3**. FP-Growth algorithm results*

Pattern description	Min. Support	Min. Confidence	Number of Patterns
7-itemset (7 feature items patterns)	50%	50%	8
6-itemset (6 feature items patterns)	86%	50%	7
5-itemset (5 feature items patterns)	93%	50%	6

According to the FP-Growth algorithm pattern mining results, there are eight patterns with ‘Agree’ or ‘Strongly Agree’ responses for seven questionnaire items in 50% learner-responses. Also, there are seven patterns with ‘Agree’ or ‘Strongly Agree’ responses for six questionnaire items in 80% learner-responses. There are six patterns with ‘Agree’ or ‘Strongly Agree’ responses for five questionnaire items in 93% learner-responses. Therefore, as per the definition of support threshold in pattern mining, it can be assumed that the most of respondents marked the questionnaire items as at least ‘Agree’. Hence the study grantees the MLA as usable.

Conclusion

The usability of a mobile learning system is very important for users to pursue academic activities as a learning medium. In this study usability of the mobile learning system was evaluated through well-established pattern mining algorithms such as Apriori and FP-Growth. Exactly 100 learners participated in the usability questionnaire after allowing them to use the system for an adequate time. According to the results, the Apriori pattern mining algorithm secured 94% system usability while the FP-Growth algorithm granted 93% system usability for the mobile learning system. On the other hand, the study proves the ability to use pattern mining approaches for assessing the usability of learning systems effectively.

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