Informing Science: the International Journal of an Emerging Transdiscipline

An Official Publication of the Informing Science Institute
InformingScience.org

Inform.nu

Volume 28, 2025

USING MACHINE LEARNING ALGORITHMS TO CLUSTER AND ANALYSE STUDENTS' ACCEPTANCE OF MOBILE LEARNING MANAGEMENT SYSTEMS

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ABSTRACT

Aim/Purpose	Technology adoption and utilization in educational institutions have increased since the pandemic. Recently, the learning management system has become crucial in the educational sector, enabling the efficient execution of online learning. In this study, we performed clustering on group learners to understand students' concerns with the mobile Learning Management System (m-LMS) based on the clusters. Furthermore, we employed classification using the technology acceptance model to evaluate the correlation among factors necessitating the acceptance and use of m-LMS.
Background	Mobile learning (m-learning) is a prevalent method of education where educational content is accessed on the go via mobile devices such as smartphones and tablets. The acceptance and deployment of mobile learning in higher education institutions has become essential in Education 4.0, a reskilling approach associated with Industry 4.0. Since the pandemic, mobile learning management systems have seen increased usage among educational institutions.
Methodology	The study modified the standard data mining and knowledge discovery methodology. This study's data set includes 446 students from the University of Education, Winneba, Ghana. The K-means algorithm was implemented to determine the number of clusters from the dataset according to the features. Subsequently, we employed a Pearson correlation coefficient heatmap to ascertain the predictability of perceived ease of use, perceived usefulness, attitude towards using,

Accepting Editor Akhil Prakash │ Received: December 3, 2024 │ Revised: March 10, May 29, 2025 │ Accepted: June 19, 2025.
Cite as: Dake, D. K., & Gyimah, E. (2025). Using machine learning algorithms to cluster and analyse students' acceptance of mobile learning management systems. *Informing Science: The International Journal of an Emerging Transdiscipline, 28,* Article 24. https://doi.org/10.28945/5596

	and actual system use of the features via the technology acceptance model. Then, a classifier was built by comparing five classification algorithms.
Contribution	A novel study on the application of a machine learning algorithm for a mobile learning management system dataset in Ghana. Implementing K-means, heatmap, and feature selection to understand learners' concerns while using m-LMS in Ghana.
Findings	The findings indicate that Cluster 1 members disagree with the benefits of using m-LMS. The disagreement cuts across all the investigated variables: perceived usefulness, perceived ease of use, attitude toward using, and actual use. Cluster 2 members agree strongly with the benefits of using m-LMS across all the investigated variables. Cluster 0, with the highest number of members, moderately agrees with the benefits of using m-LMS. In addition, a strong correlation exists between perceived ease of use, perceived usefulness, and attitude towards using. Furthermore, the attitude towards using was predicted by perceived usefulness. However, there was an unreliable relationship between attitude towards using and actual system use.
Recommendations for Practitioners	Cluster segmentation of students using m-LMS facilitates the formulation of an implementation policy, enabling educational authorities to address the issues contributing to student dissatisfaction with m-LMS. Furthermore, the results imply that, even though students desire to use a mobile learning management system, they are not using it. It means there are challenges surrounding using the mobile learning management system at the University of Education, Winneba.
Recommendations for Researchers	The use of K-means, elbow function, and correlation heatmap in the technology acceptance model for variable correlation test reveals detailed predictability patterns that necessitate a new research direction using machine learning.
Impact on Society	Stakeholders in education should embrace and support machine learning implementation in the educational sector to reveal data patterns for improved teaching and learning.
Future Research	Subsequent research will broaden the data on mobile learning management systems to include the majority of tertiary institutions in Ghana. The data will be indicative, allowing for the generalisation of inferences regarding national policy directions on m-LMS.

Keywords	mobile learning management system, machine learning, technology acceptance model, K-means, sequential minimal optimization algorithm, correlation heatmap

INTRODUCTION

The rise in mobile device usage has impacted essential sectors of the global economy, including education. A mobile phone is a portable device used primarily for communication purposes (Chan, 2015; Grantz et al., 2020). According to Statista (2024), the number of smartphone users in 2024 is 4.54 billion. They projected smartphone usage to reach 6.2 billion by 2029. The data also indicates that most smartphone users are literate and of school age (Alhassan et al., 2018; Alsayed et al., 2020; Statista, 2024). The COVID-19 pandemic prompted significant educational reforms, and the utilisation of digital technologies, such as mobile phones, was crucial to successful learning outcomes. Institutions worldwide rapidly transitioned to online teaching and learning methods, with deprived institutions having serious infrastructure and technical support challenges due to the knee-jerk response to the pandemic (Adedoyin & Soykan, 2023; Maatuk et al., 2022). The traditional method of lesson delivery was abandoned during the epidemic, with information and communication technologies (ICTs) pivotal in facilitating the learning process (Chiu et al., 2021; Lemay et al., 2021; Maatuk et al., 2022). The complexity and uncertainty of the pandemic prompted a global discourse on future preparedness and the integration of ICTs in education. Students who are primarily at the centre of the learning process in readiness for unforeseen eventualities must adjust and embrace diverse technologies with support systems created by educational authorities for an inclusive transformation in teaching and learning (Bartolic et al., 2022; Fujita, 2020; Geurts et al., 2024; Murtonen et al., 2024).

Mobile learning (m-learning) is a prevalent method of education where educational content is accessed on the go via mobile devices such as smartphones and tablets (Crompton & Burke, 2018; Heflin et al., 2017). Mobile technology inception and usage in education has created flexibility in the learning process, making it especially more essential in an era of growing student populations and unplanned, tragic situations, such as the recent epidemics. Mobile technology in education is becoming pertinent in an era characterised by artificial intelligence (AI), tactile internet (TI), virtual reality (VR), augmented reality (AR), and the Internet of Things (IoT). The emergence of these disruptive technologies, coupled with the advancements in wireless technology such as 5G and 6G networks, has created a positive trend in pedagogy (Bongomin et al., 2020; Frizzo-Barker et al., 2020; Radu, 2020). The acceptance and deployment of mobile learning in higher education institutions has become essential in Education 4.0, a reskilling approach associated with Industry 4.0. The educational paradigm with Education 4.0 is integral to futuristic labour markets, making students' acceptance of mobile learning a necessity (de Souza & Debs, 2024; Mian et al., 2020; Moraes et al., 2023). As shown in Figure 1, smartphones are the second fastest growing devices with a compound annual growth rate (CAGR) of 7%. Aside from devices, the fastest-growing technology is Machine-to-Machine (M2M) communication. Educational policies and strategies must evolve to prioritise m-learning, accompanied by research to comprehend students' grievances with its adoption.

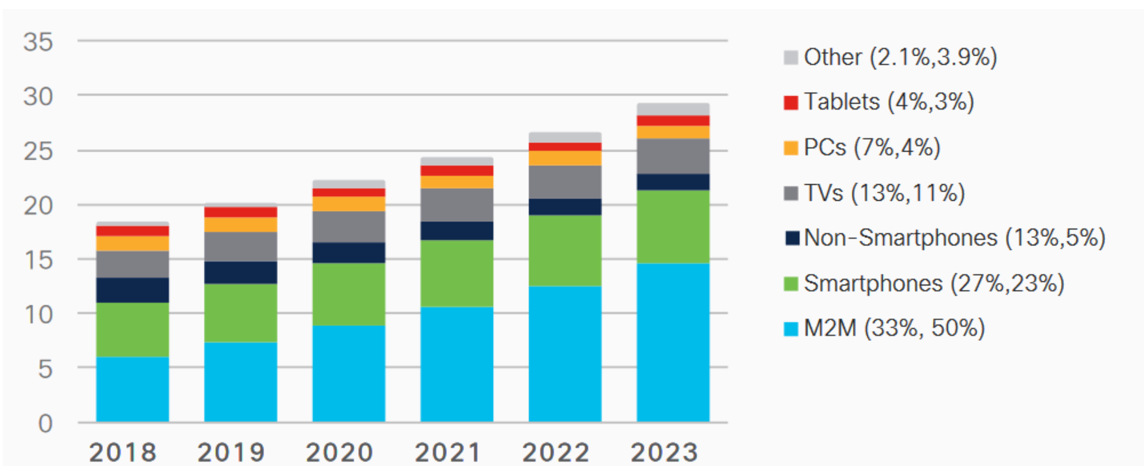

Figure 1. Global device and connectivity growth (source: Cisco, 2020)

The Learning Management System (LMS) is a web-based application designed to create, manage, and distribute educational content. LMS is an essential tool that promotes efficient learning and development (Bradley, 2020; Saroia & Gao, 2019; Turnbull et al., 2021). The LMS, an e-learning platform, includes extensive features that improve instructional delivery through meaningful pedagogical activities. LMS platforms support inclusive education, collaborative learning, responsive communication, and discussion segments comparable to traditional classroom settings (Al-Dhief et al., 2024; Bervell & Umar, 2020). The adoption of an LMS has numerous benefits over traditional learning approaches. These include access to a greater range of resources, independent learning, cost-effectiveness, and convenience with flexibility (Al-Dhief et al., 2024; Müller & Mildenberger, 2021). Mobile Learning Management System (m-LMS) refers to the accessibility of LMS using mobile devices. Using m-LMS transcends locations and offers flexibility in online teaching and learning (Saroia & Gao, 2019; Sulaiman, 2024).

Machine learning (ML) in education has recently emerged as a tool for revealing previously unseen patterns in data (Martins et al., 2024; Sanusi et al., 2023). ML, a vital subset of artificial intelligence (AI), uses algorithms to mine educational data to enhance the learning process. Clustering in ML involves feature groupings of similar data instances without class labels (Lopez et al., 2018; Shutaywi & Kachouie, 2021). Unsupervised clustering has been used primarily in educational contexts for responsive student counselling, learning style analysis, project groupings, students' performance evaluation, and learner engagement assessment (Dutt et al., 2015; Mohamed Nafuri et al., 2022). Contrarily, classification is a supervised learning technique that uses class labels for regression and prediction. In educational settings, classification has been used primarily to model learner academic achievement, student behaviour, retention prediction, automated grading, decision support systems, and recommender systems (Bakhshinategh et al., 2018; Quadri, 2020). Reinforcement learning (RL), another fundamental ML method that allows software agents to learn through trial and error while accruing rewards, has a significant use case in Education 4.0. Personalised learning, automated course restructuring, an online book recommendation system, and automated grading are some of the most common applications of RL in education (Fahad Mon et al., 2023; Memarian & Doleck, 2024).

The primary objective of this study is to employ machine learning to cluster students' acceptance of mobile learning management systems, emphasising the cohesion and correlation among members of each cluster. This study aims to comprehend students' concerns regarding the implementation of m-LMS post-pandemic and to provide solutions for educational reform. The gaps in the literature indicate that ML strategies for revealing hidden trends in m-LMS usage among Ghanaian students are unavailable. Furthermore, there is insufficient work on investigating TAM variables using ML rather than statistical approaches. In line with the objectives, the following research questions guided the study:

(1) How many clusters from the m-LMS dataset are formed using the elbow method?
(2) What are the cluster groupings? To what extent do the cluster members vary?
(3) What is the correlation among the variables? What is the intensity of the correlation?
(4) Which classification algorithm performs best in building a predictive model for future cluster members?

This study's primary contributions encompass:

(1) A novel study on the application of a machine learning algorithm for the m-LMS dataset in Ghana.
(2) The implementation of K-means, heatmap, and feature selection to understand learners' concerns while using m-LMS in Ghana.

The remainder of the paper is structured as follows. The next section is the literature review, which is followed by the analysis of the methodological approach. Then the results and analysis are presented. The findings are then examined and correlated with the existing research. Finally, the conclusion is presented, along with the study's limitations.

LITERATURE REVIEW

The review is divided into three sections. The first section examines the technology acceptance model (TAM) in m-LMS studies. The second section of the review delves into basic research on m-LMS. The final section of the review investigates m-LMS studies that used machine learning methods.

TECHNOLOGY ACCEPTANCE MODEL

The technology acceptance model (TAM) (Davis, 1989) has been extensively utilised in the adoption of new technologies and in customer attitudes toward embracing them. In addition to the TAM for testing user attitudes, other models such as the unified theory of acceptance and use of technology (UTAUT), innovation diffusion theory (IDT), and the theory of planned behaviour (TPB) are commonly employed (Ahmad Wani & Wajid Ali, 2015; Armitage & Conner, 2010; Williams et al., 2015).

As shown in Figure 2, the TAM's perceived usefulness (PU) and perceived ease of use (PEOU) are two informed beliefs that predicate theory on system usage. The PU and PEOU are also affected by external variables, $x_1 \dots x_n$, that give specifics on the degree of acceptance and usage. In this research, TAM is used because it is a clear and concise framework, it has a high ability to predict user behaviour accurately, and it is widely applicable in several domains (Legris et al., 2003; Na et al., 2022; Wang et al., 2023).

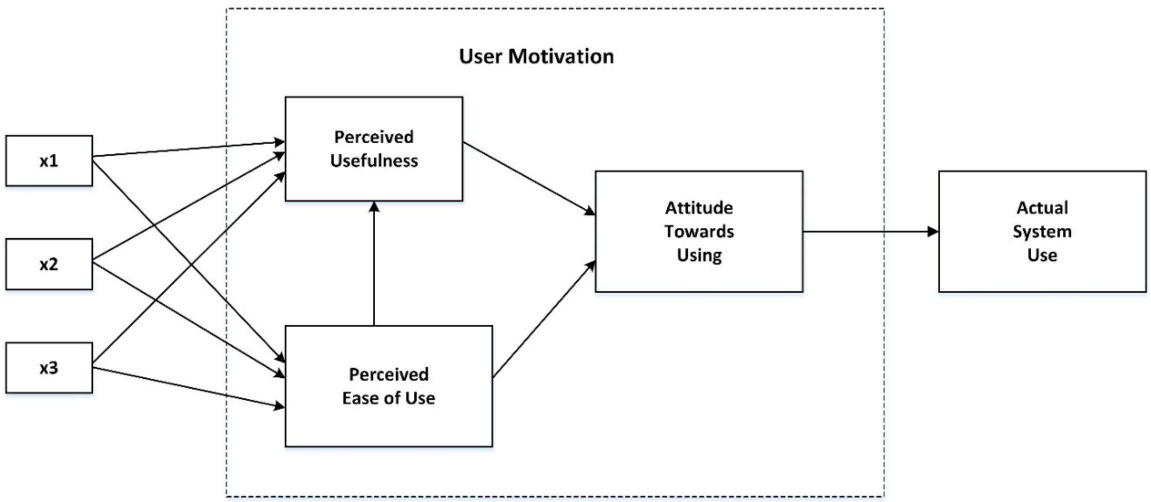

Figure 2. Technology Acceptance Model (TAM) (Davis, 1989)

BASIC RESEARCH

The basic research regarding m-LMS largely examines the behavioural intents of students to utilise mobile learning management systems. The data acquired in such research aims to examine integrated correlations among learners' satisfaction, perceived usefulness, perceived ease of use, continuation intention, expectation-confirmation, and actual usage of m-LMS. Joo et al. (2016) investigated 222 students from the Korean online university about their actual usage of m-LMS based on the TAM model. Their findings show that, whereas perceived ease of use predicted perceived usefulness, there was no correlation between perceived usefulness and expectation-confirmation. Furthermore, continuation intention was found to be predictive of actual m-LMS usage. Alfalah (2023) collected data on 258 students from Saudi Arabia and examined factors influencing students' adoption of m-LMS based on the extended UTAUT model. Performance expectancy, effort expectancy, and the influence of lecturers significantly affect behavioural intention, while facilitating conditions are negligible. Moreover, performance expectancy was significantly affected by perceived mobile value and academic relevance.

Ikhsan et al. (2023) predicted the use of m-LMS by using 500 students from Nusantara University in Indonesia based on the extended UTAUT model. The findings demonstrate that performance, social influence, hedonic motivation, habit, facilitating conditions, perceived satisfaction, and effort expectancy influenced the intention to utilise m-LMS. Furthermore, behavioural intentions, facilitating situations, habits, and hedonic incentives all had an impact on actual m-LMS use. Shin and

Kang (2015) investigated students' acceptance of m-LMS among 1,117 undergraduate students in a South Korean online university based on the TAM and the information system success (ISS) models. The findings indicate that self-efficacy, personal innovativeness, and social factors directly influence perceived ease of use. Nonetheless, subjective norm and relative advantage did not affect perceived ease of use. Saroia and Gao (2019) explored the utilisation of m-LMS among 130 university students in Sweden based on the TAM. The findings show that perceived usefulness positively influences behavioural intention and attitude towards use. Academic relevance and perceived mobility value also influenced perceived usefulness. The studies examined show the relevance of perceived usefulness (PU), perceived ease of use (PEOU), attitude towards using (ATU), and actual system use (AU) of how the users accept a new technology. Furthermore, in the context of m-LMS, the variable correlation between user motivation (PU, PEOU, ATU) and actual system usage (AU) in TAM aids in forecasting students' acceptance of m-LMS to enhance teaching and learning.

MACHINE LEARNING

A comprehensive examination of the literature on machine learning in m-LMS produced no results (Table 1). Learning management systems (LMS), mobile learning platforms, and their use by students are the primary focus of machine learning research in predicting diverse hypotheses. Kuadey et al. (2022) implemented ML algorithms on 280 students from a technical university in Ghana (Ho Technical University) to predict students' continued use of LMS. They used the following classification algorithms: random forest (RF), rule learner (OneR), lazy classifier (IBk), naïve bayes (NB), AdaBoost, and the sequential minimal optimization (SMO) algorithm. SMO outperformed in forecasting the continuance intention to use (CIU) LMS based on the availability of resources (AR) and effort expectancy (EE). NB performed better at predicting CIU based on computer self-efficacy (CSE). RF performed better at predicting CIU based on perceived enjoyment (PE) and social influence (SI). IBk performed best in predicting CIU based on performance expectancy (PEX) and facilitating conditions (FC).

Table 1. Summary of literature review – machine learning

Study	Dataset	Algorithms	Best performing algorithm	Findings
Kuadey et al. (2022)	Ho Technical University (280 students)	RF, OneR, IBk, NB, AdaBoost, SMO	RF, IBk (accuracy = 99.64%)	They concluded that learners' intention to continuously use LMS is influenced by the availability of resources, including internet reliability, computer access, and internet cost.
Alshurideh et al. (2023)	British University in Dubai and the University of Fujairah (448 students)	BayesNet, LWL, DT, OneR, AdaBoost, LRC	DT (accuracy = 88.31%)	Their findings indicate that perceived usefulness plays the most crucial role in influencing students' intention to use m-learning.
Almaiah et al. (2021)	Five universities in Jordan (397 students)	RF, Bagging, SMO, IBk, NB, rule-learner (PART).	RF, IBk (accuracy = 87.06%)	The results of their study show that perceived ease of use, usefulness, effectiveness, efficiency, enjoyment, behavioural intention to use, and utilisation predict mobile learning application acceptance by 87.06%.

Alshurideh et al. (2023) utilised BayesNet, lazy classifier (LWL), decision tree (DT), rule learner (OneR), AdaBoost, and logistic regression classifier (LRC) to forecast the correlation between evaluated hypotheses employing the TAM model on 448 students from the British University in Dubai and the University of Fujairah. Their findings reveal that the DT outperforms other classifiers in predicting the PEOU and PU of m-learning using the variables social impact and expectation-confirmation, respectively. OneR and DT surpass other classifiers in forecasting satisfaction based on expectation-confirmation. DT once again outperforms other classifiers in predicting continuous intention based on variables PU, PEOU, and satisfaction. The LRC outperforms other classifiers at predicting actual use based on the continuous intention variable. Almaiah et al. (2021) investigated students' acceptance of mobile learning applications during the pandemic using ML algorithms. They implemented the following classifiers to test the hypothesis among the factors: RF, Bagging, SMO, IBk, NB, and rule-learner (PART). The results show that the IBk algorithm performs best in predicting perceived enjoyment (PEJ) by the factor PEOU. RF and IBk again demonstrate the highest accuracy in predicting behavioural intention to use (BI) based on PEOU, PEJ, and PU factors. The RF performs better in predicting PU based on the PEOU factors. The NB performs better in predicting effectiveness based on the construct of perceived enjoyment.

RESEARCH METHODOLOGY

As shown in Figure 3, the study modified the standard data mining and knowledge discovery methodology (Fayyad et al., 1996) by embedding clustering inside the methodological procedure. The data mining process consists of the following steps sequentially: data selection, data pre-processing, cluster formation, pattern analysis, evaluation using machine learning metrics, and knowledge discovery.

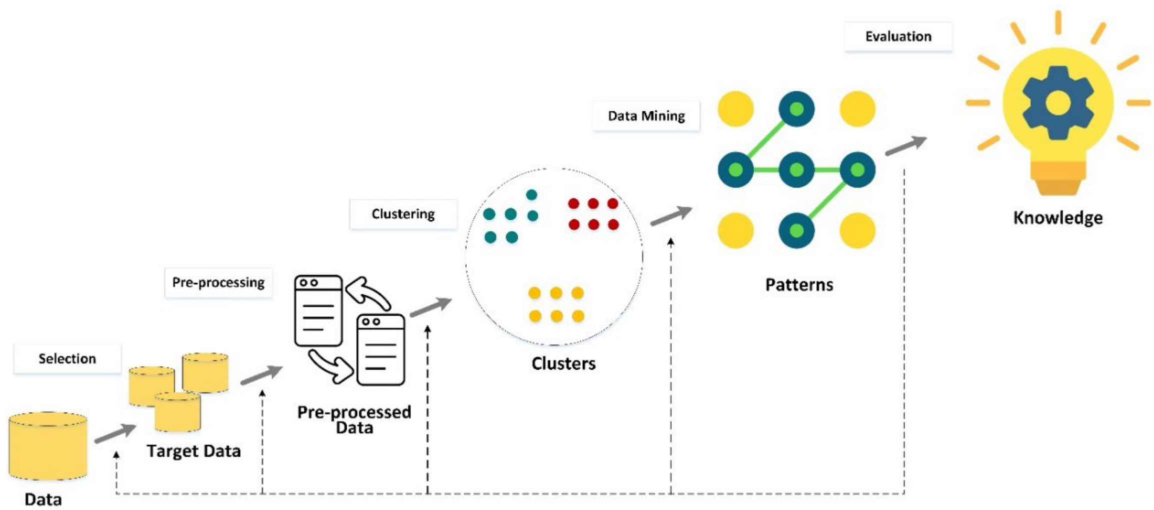

Figure 3. Knowledge discovery methodology

DATA COLLECTION

Students at the University of Education, Winneba, provided the information that was gathered for this study for the purpose of collecting data. Generally, the data collected was from students at the Faculty of Science Education (FSE). The FSE comprises the following departments: chemistry education, physics education, ICT education, mathematics education, biology education, integrated science education, and agriculture education. The primary target of students, however, was on those pursuing a Bachelor's Degree in Information and Communication Technology Education (BSc ICT Education) because of learners' availability to the researchers. The students were consequently classified as ICT Education students and non-ICT Education students. The study employed a non-probability sampling technique, specifically convenient sampling, for sample collection. Convenience sampling was employed due to the students' availability and accessibility to the researchers. Approval was sought from the Research Ethics Board of the University of Education, Winneba, in administering the Google form. Respondents were required to consent to an ethics form before completing the questionnaire. Throughout the process, the confidentiality, nondisclosure, and privacy of responders were rigorously upheld. Consequently, no respondent can be linked to the collected data. A total of 446 responses were received.

Research Instrument

The primary focus was on clustering the construct based on the literature reviewed. We adopted a 6-point Likert rating scale to test the construct, ranging from "strongly disagree = 1" to "strongly agree = 6". The questionnaire consists of the following constructs: perceived usefulness (PU), perceived ease of use (PEOU), attitude towards using (ATU), and actual system use (AU). In addition, the respondent's demographic information, including age and gender, was added. The revised constructs were taken from the works of Davis (1989), Sadeck (2022), Al-Emran et al. (2020), and Almaiah and Al-Khasawneh (2020). As shown in Figure 4, the study focused on user motivation (PEOU, PU, ATU) and behavioural response (AU) based on the TAM.

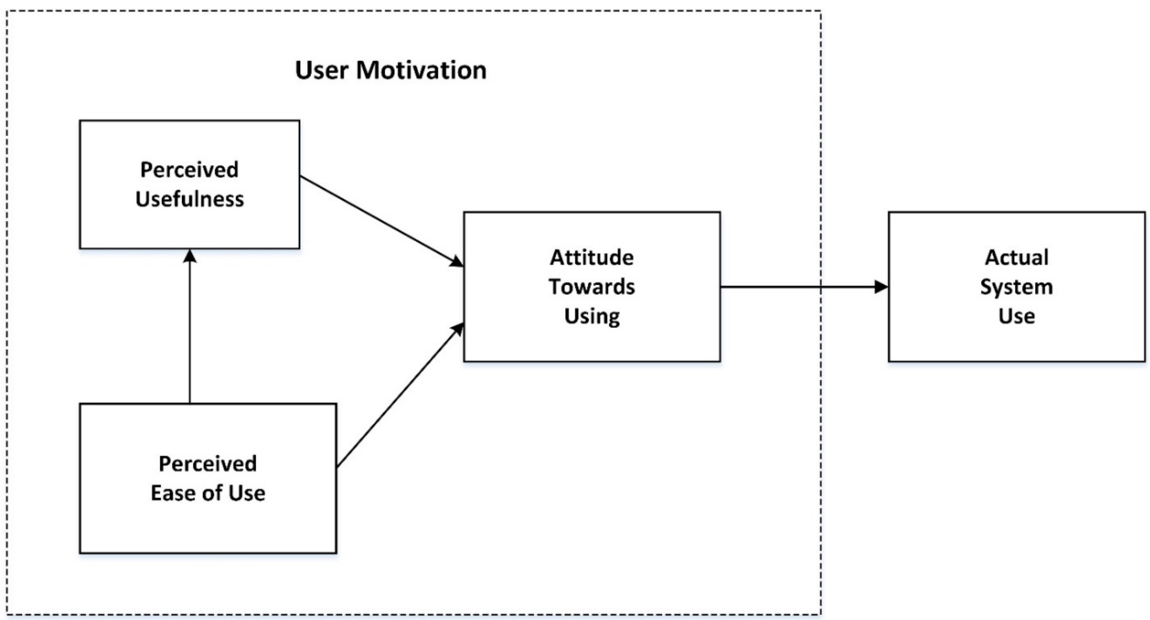

Figure 4. Modified TAM for study

The variables tested and questions are illustrated in Table 2. As seen in Table 2, PU, PEOU, ATU, and AU were investigated using machine learning.

Table 2. Variables investigated based on the TAM

Variable	Question
Perceived Usefulness (PU)	m-LMS enables me to accomplish tasks more quickly.
	m-LMS enhances my effectiveness.
Perceived Ease Of Use (PEOU)	My interaction with m-LMS is clear and understandable.
	Learning to operate m-LMS is easy for me.
	m-LMS is convenient and user-friendly.

Variable	Question
Attitude Towards Using (ATU)	m-LMS makes my work more interesting.
	m-LMS is fun.
	I like working with m-LMS.
Actual System Use (AU)	I use m-LMS on a daily basis.
	I use m-LMS frequently.

CLUSTERING

The K-means algorithm is implemented in this study. K-means is an unsupervised ML algorithm that performs well with numeric datasets. The objective of K-means clustering is to partition a set of data points into several clusters, ensuring that the data points within each cluster exhibit greater similarity (Ahmed et al., 2020; Yuan & Yang, 2019). The K-means clustering operates by identifying k cluster centroids that minimise the sum of squared Euclidean distances between the centroids and their respective cluster members. The individuals in a cluster are assigned to the cluster nearest to the cluster mean (Aldino et al., 2021; Huang, 1998; Sinaga & Yang, 2020). As shown in Figure 5, the K-means algorithmic steps follow the provision of the initial value for k, recalculating centroids for cluster membership by repeating steps 4 and 5.

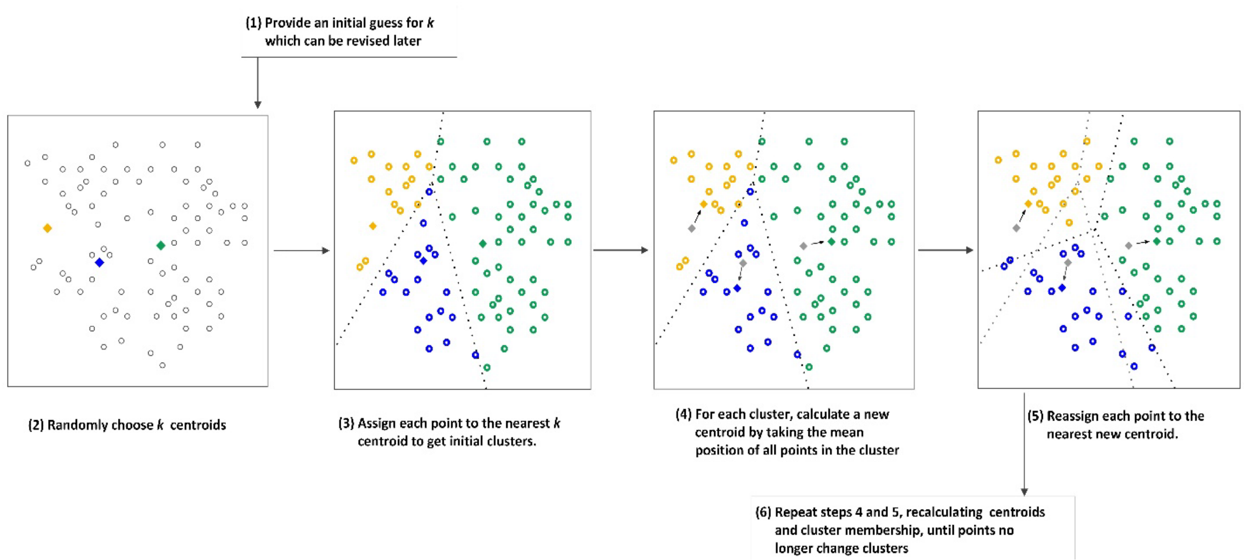

Figure 5. K-means clustering algorithm (Google for Developers, 2024)

K-means algorithmically divides n instances of data into k clusters where $k < n$, assigning each instance to the cluster with the nearest mean. Equation 1 illustrates the implementation of the K-means algorithm utilising Euclidean distance to ascertain the separation between two data points.

$$Dist_{qp} = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{1}$$

Equation 1 produces a multivariate mean in Euclidean space by representing sample data points within an n-dimensional feature space with q and p.

CLASSIFICATION, FEATURE SELECTION, AND PERFORMANCE METRICS

Classification is employed to forecast the prospective cluster groups of incoming students. The study utilised the following machine learning algorithms based on their performance in the literature review: Decision Tree (DT), Naïve Bayes (NB), AdaBoost, Random Forest (RF), and the sequential minimal optimization (SMO) of support vector machine (SVMs) (SMO-SVM). Even though the IBk from the literature review gave impressive accuracy results, it doesn't build a model during the training phase. This affects the reliability of its performance during classification. The Chi-squared test is conducted to identify the predominant features that affected the cluster predictions. The Chi-square test is a statistical technique that assesses the significance of the association between input variables and a target variable (Franke et al., 2012; Thaseen et al., 2019). Equations 2–5 illustrate the classification performance metrics, including accuracy, precision, recall, confusion matrix, and F-measure, which were analysed to identify the optimal algorithm. In the equation, True_N, True_P, False_N, and False_P represent the number of true negatives, true positives, false negatives, and false positives, respectively.

$$\text{Accuracy} = \frac{\text{True\_P} + \text{True\_N}}{\text{True\_P} + \text{False\_P} + \text{False\_N} + \text{True\_N}} \quad (2)$$

$$\text{Precision} = \frac{\text{True\_P}}{\text{True\_P} + \text{False\_P}} \quad (3)$$

$$\text{Recall} = \frac{\text{True\_P}}{\text{True\_P} + \text{False\_N}} \quad (4)$$

$$\text{F} - \text{measure} = \frac{2 \text{ x Precision x Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

SIMULATION RESULTS

In the simulation, we used Jupyter Notebook, an open-source interactive web-based computing program that combines visualisations, equations, narrative text, and live code. In addition, we used Continuum Analytics' Anaconda Python distribution, SciPy, Pandas, NumPy, Matplotlib, and Scikit-learn.

CLUSTER FORMATION USING THE ELBOW METHOD

Research Question 1: How many clusters from the m-LMS dataset are formed using the elbow method?

In response to RQ1, the study used the elbow approach for optimal cluster identification. The elbow is a point of inflexion where the Within-Cluster Sum of Squares (WCSS) difference begins to decrease. As shown in Figure 6, the point of inflexion begins to drop sharply when $k = 2$. However, the optimal cluster is selected at $k = 3$, where the elbow of the arm occurs. The number of clusters formed, therefore, is 3. Determining the number of clusters is relevant in knowing the number of groups among a given dataset and aids in providing the same solution for each group. In addition, cluster groupings enable educators to make informed decisions about each member within the cluster. It therefore narrows the solution approach in identifying cluster member difficulties and strengths.

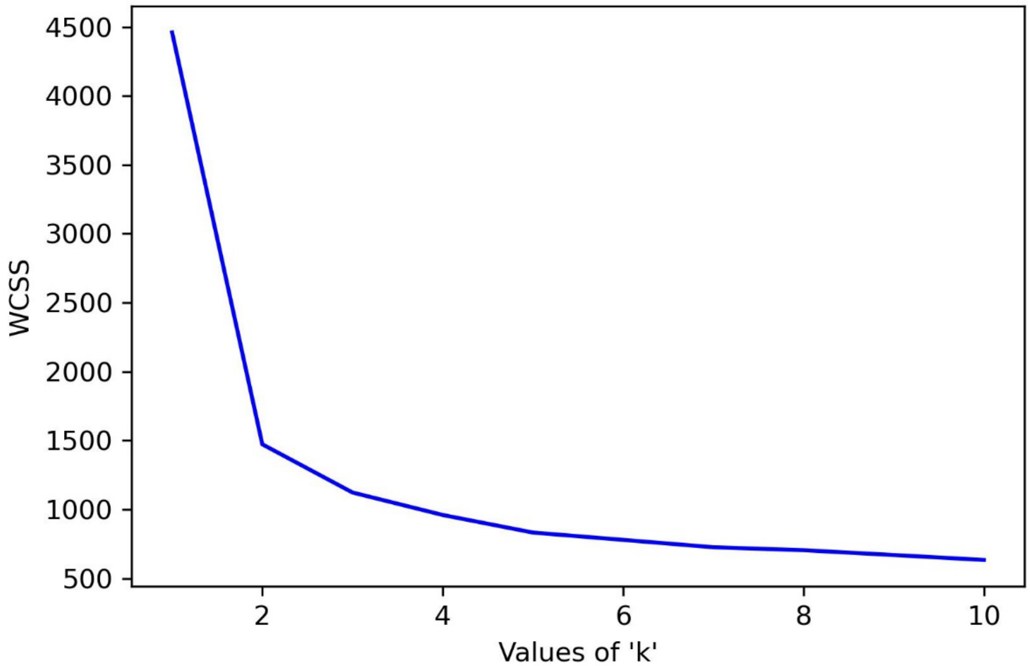

Figure 6. Elbow method used to determine the optimal cluster

Research Question 2: What are the cluster groupings? To what extent do the cluster members vary?

In response to RQ2, the study first determined the number of cluster members, then addressed cluster variations based on variables, and then used Principal Component Analysis (PCA) to improve and depict cluster segmentation. As seen in Figure 7, Cluster 0 has the highest number of members (222), followed by Cluster 2 (130) and Cluster 1 (94). In percentages, Cluster 0 has 49.78%, followed by Cluster 2 at 29.15%, and Cluster 1 at 21.07%.

As shown in Figure 8, Cluster 1, which has the least number of members (21.07%), disagrees with the benefits of using m-LMS. The disagreement cuts across Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Using (ATU), and Actual Use (AU). These students have struggled to use the m-LMS and are dissatisfied with its continued use. Even though they are the smallest group, this cluster of learners needs urgent intervention with options provided to improve their effective engagement in the learning process.

Cluster 1 members are at risk of failing in the course if their views are not heard regarding the reasons they are dissatisfied with m-LMS usage for teaching and learning. Cluster 2 members, with a moderate membership of 29.15%, strongly agree with the benefits of using m-LMS. The agreement cuts across PU, PEOU, ATU, and AU. These cluster groups are comfortable with using m-LMS and support its continual usage for effective lesson delivery. Cluster 0, with the highest membership (49.78%), moderately agrees with the benefits of using m-LMS. This group of learners is uncomfortable with fully using m-LMS and will need support systems to strongly agree with its usage.

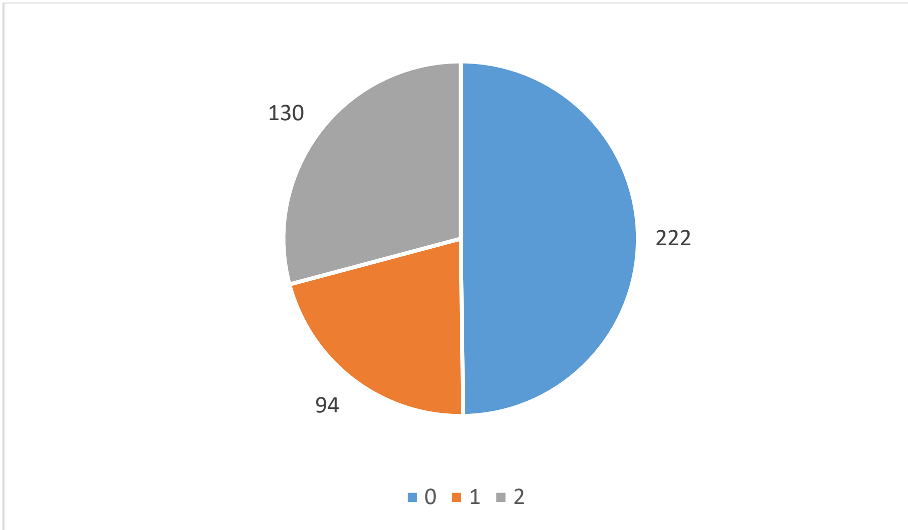

Figure 7. Cluster members

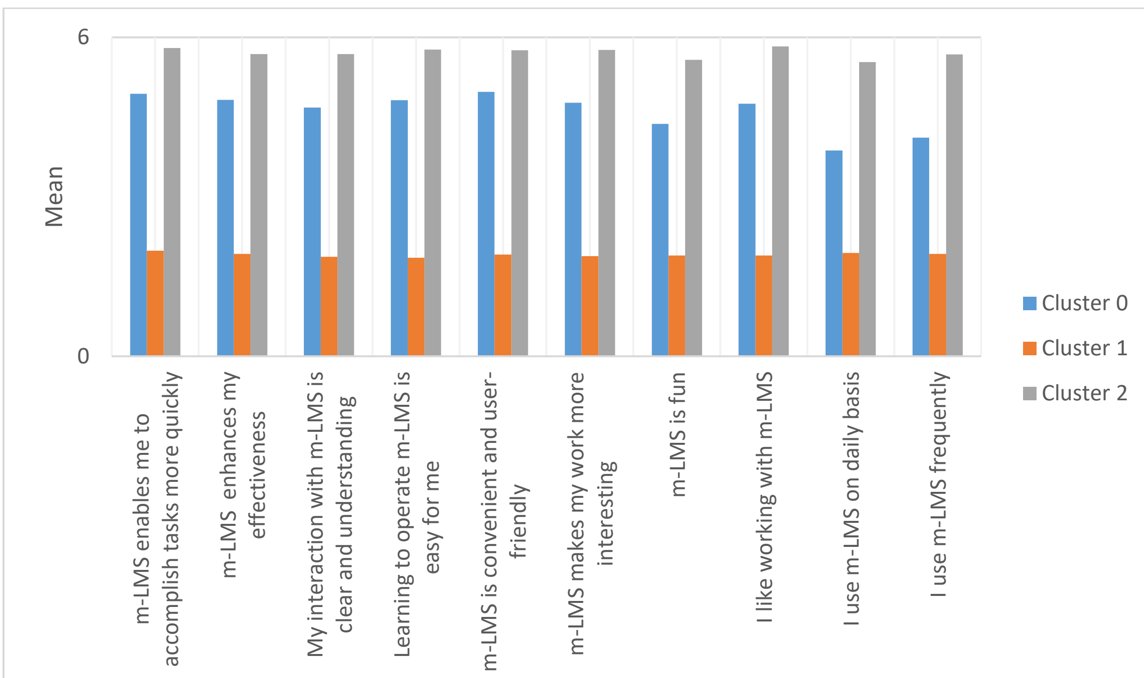

Figure 8. Cluster variation

As shown in Figure 9, Cluster 0, which has the highest number of members, is visually dispersed. This implies that members of Cluster 0 hold varying opinions regarding the adoption of m-LMS, posing a unique challenge for instructors in devising a single solution for these members. There is much cohesion among Cluster 2 members. Cluster 2 members largely agree with the benefits of using m-LMS. This cohesion suggests a cluster group that can benefit from the same pedagogical process. Cluster 1 members have better cohesion than Cluster 0, but are loosely dispersed compared to Cluster 2. Tailoring of pedagogy towards this cluster group must be carefully considered. Most Cluster 1 members strongly disagree with the benefits they derive from using m-LMS.

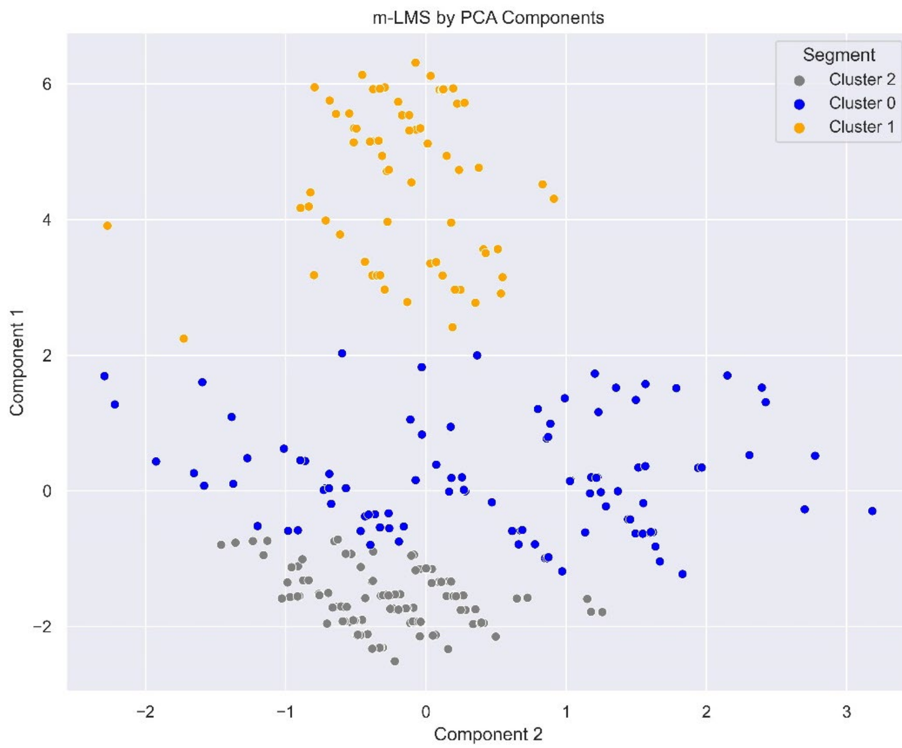

Figure 9. m-LMS cluster groupings using PCA

Research Question 3: What is the correlation among the variables? What is the intensity of the correlation?

The correlation heatmap shown in Figure 10 is a matrix that graphically illustrates the correlation among the variables. The findings are based on the Pearson correlation coefficient matrix. The correlation between the variables ranges from -1 to 1, with a colour spectrum extending from light grey to deep blue. The deep blue at 1 signifies a perfect correlation between the variables, whereas the lightest grey at -1 denotes a perfect negative correlation between the variables. The medium 0 denotes no correlation between the variables. Very strong correlation (0.8-1), strong correlation (0.7-0.79), moderate correlation (0.5-0.69), and weak correlation (0-0.49). The variable correlation and prediction are based on the questions asked across each variable, as illustrated in Table 2. The minimum Pearson correlation coefficient matrix represents the intersections across the questions. The questions represent PU, PEOU, ATU, and AU. The test shows that variables in PEOU have a strong positive relationship with variables in PU. The minimum value is 0.79.

Therefore, perceived ease of use (PEOU) predicted perceived use (PU). The variables in PEOU directly and positively relate to ATU. The minimum value is 0.77. Therefore, a strong correlation exists between perceived ease of use (PEOU) and attitude towards using (ATU). There is a strong relationship between the variables of PU and ATU. This means that perceived usefulness (PU) predicts attitude towards using (ATU). The minimum value is 0.74. There is a moderate relationship between ATU and AU. It means that students are not really using the m-LMS. The minimum occurs at 0.66. This means that students slightly disagree with the notion that m-LMS is convenient and user-friendly, m-LMS makes their work more interesting, and m-LMS is fun.

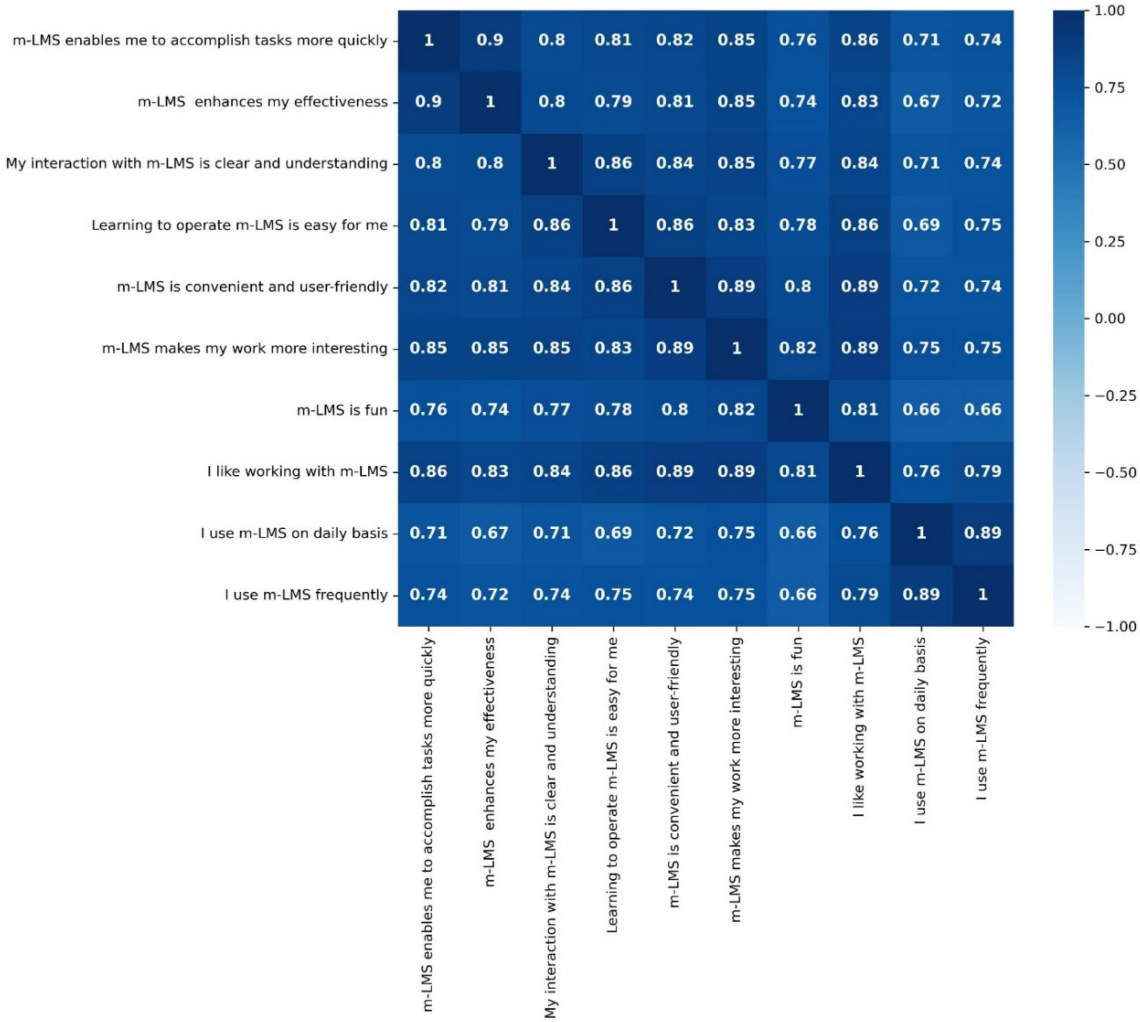

Figure 10. Heatmap of Pearson correlation coefficient matrix

Research Question 4: Which classification algorithm performs best in building a predictive model for future cluster members

In addressing RQ4, we evaluated the efficacy of the classification algorithms based on accuracy, F-measure, ROC-AUC, and the confusion matrix. Furthermore, we employed the Chi-square feature selection method to identify the most significant factors affecting cluster predictions. As shown in Table 3, the Sequential Minimal Optimization of Support Vector Machine (SMO-SVM) algorithm has the highest accuracy (99.55%), followed by the naïve bayes (NB) algorithm (95.74%). The algorithm with the least performance is the AdaBoost multi-classifier (83.18%).

Table 3. Performance of the classifiers

Classifier	Accuracy	F-measure	ROC-AUC
Decision Tree (DT)	91.70	0.917	0.953
Naïve Bayes (NB)	95.74	0.958	0.991
AdaBoost	83.18	0.824	0.939
Random Forest (RF)	95.52	0.955	0.998
Sequential Minimal Optimization of Support Vector Machine (SMO-SVM)	**99.55**	0.996	0.998

We also investigated the confusion matrix of the classification algorithms. As shown in Figure 11, the SMO-SVM shows dominance by misclassifying only 2 of the cluster 0 members in cluster 2.

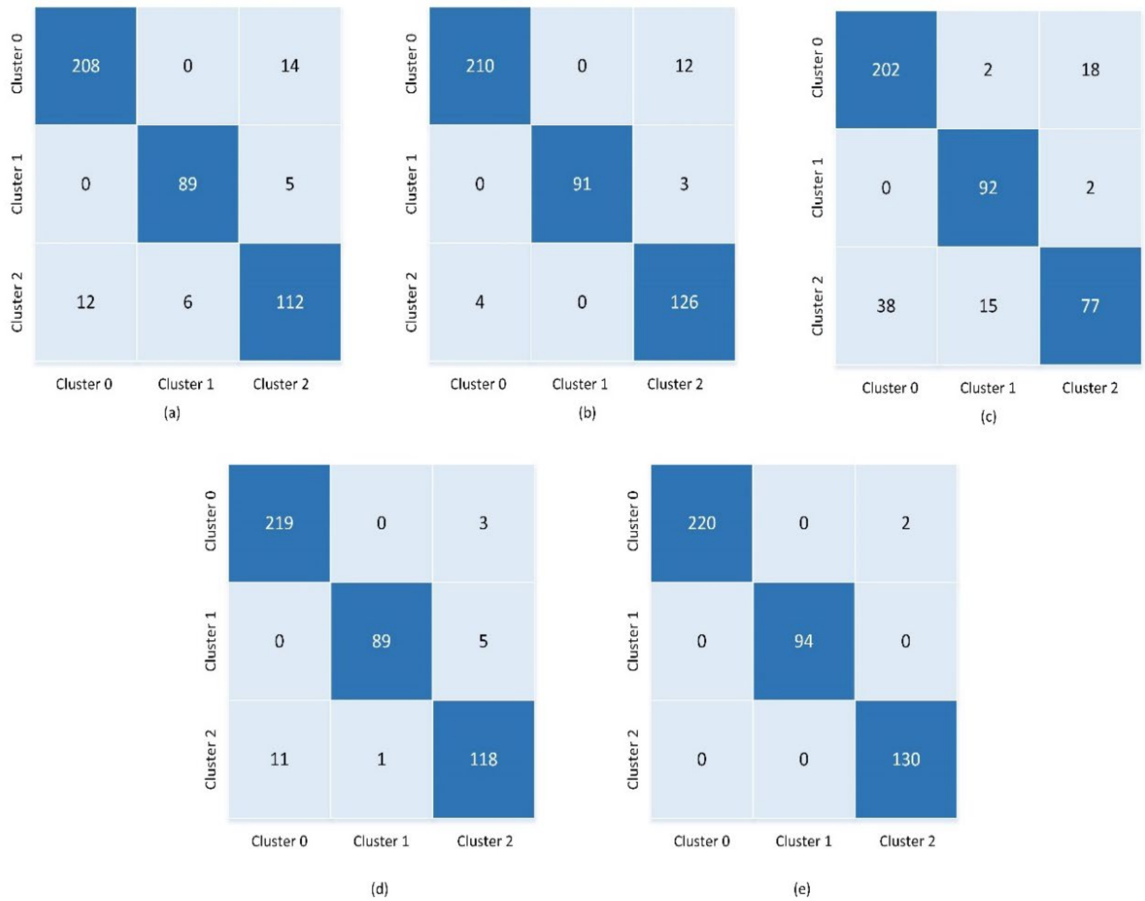

Figure 11. Confusion matrix of classifiers
(a) DT (b) NB (c) AdaBoost (d) RF (e) SMO-SVM

The AdaBoost classifier, which is the worst-performing, incorrectly classified 2 of its cluster 0 members as cluster 1 and 18 members as cluster 2. The AdaBoost classifier also misclassified 2 of its Cluster 1 members as Cluster 2. In addition, AdaBoost misclassifies 38 of its Cluster 2 members as Cluster 0 and 15 as Cluster 1.

Figure 12 shows the dominant cluster predictors in descending order. The dominant predictors indicate the most influential questions that affected the clustering and the classification model. There is a need for educators using m-LMS at the University of Education, Winneba, to pay extra attention to the most significant variables in providing a solution to learners' disinterest in using m-LMS. The top four most relevant features, which indicate how cluster members are categorised, are "I like working with m-LMS," "m-LMS makes my work more interesting," "m-LMS enables me to accomplish tasks quickly," and "My interaction with m-LMS is clear and understanding." The two least relevant features are "m-LMS is fun" and "I use m-LMS on a daily basis."

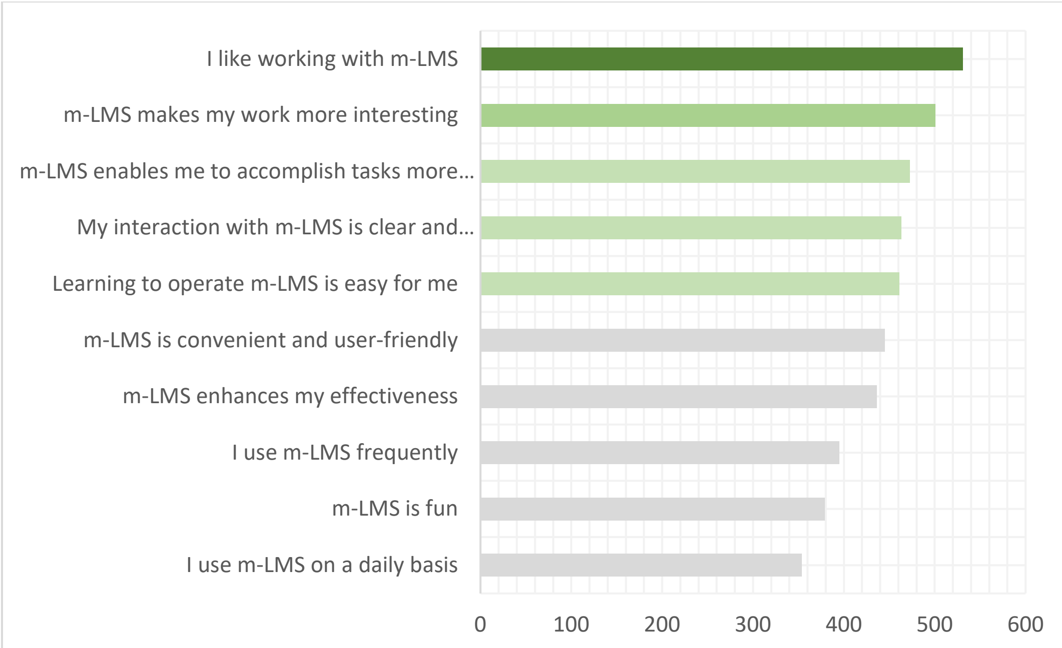

Figure 12. Feature importance using Chi-square evaluator

DISCUSSION AND FINDINGS

The research examined mobile learning management systems (m-LMS) and their acceptability by university students in Ghana. The main aim of the work is to utilise machine learning to ascertain correlations among TAM variables. The variables of interest were user motivation and actual system utilisation. There has been a decade of research on the TAM and how people adopt and use new technologies. The majority of research utilising the TAM predominantly employs statistical methods to ascertain variable correlations and propose strategies for technology acceptance.

This study first utilised clustering to group the kinds of students who answered the questionnaire. The first group of students identified using K-means disagreed with the benefits of utilising m-LMS, the second group, which constitutes the majority, is not completely convinced of the benefits of m-LMS, and the third group is comfortable with m-LMS and actively promotes its use. The diverse groups show an implementation policy with m-LMS, with educational authorities taking steps to address the challenges with each group. Cluster 1 members who are primarily at risk and totally disagree with m-LMS usage are of the view that m-LMS does not help in accomplishing tasks easily, m-LMS is not user-friendly, m-LMS implementation is ineffective, and m-LMS is complex to use. Secondly, we generated a heatmap of the variables to determine the correlation between them. The person heatmap shows a trend where perceived ease of use (PEOU) predicts perceived usefulness (PU) and attitude towards using (ATU). PU intends to predict ATU. However, the relationship between ATU and actual use (AU) has a moderate correlation coefficient, rendering it unreliable. The findings align with the study conducted by Joo et al. (2016), where PEOU predicted PU in their research on actual usage of m-LMS for online studies. It also confirms Shin and Kang's (2015) findings, which show that PEOU predicts PU when using m-LMS in online learning for learner achievement and satisfaction. This implies that students who perceive using m-LMS as effortless believe it can help them with their academic work.

The second aspect of the study presented a machine learning model designed for the predictive clustering of new students. Predictive clustering is important in applying the same pedagogical strategies to new students based on the originally formed clusters. The performance of the following classification algorithms was tested in building the final model: Decision Tree (DT), Naïve Bayes (NB), AdaBoost, Random Forest (RF), and the SMO-SVM. The SMO-SVM algorithm outperforms the other classifiers for accuracy, F-measure, ROC-AUC, and confusion matrix. The confusion matrix clearly demonstrates the dominant performance of the SMO-SVM classifier in correctly classifying cluster members. The SMO-SVM achieved an accuracy of 99.55, followed by the Naïve Bayes (NB) algorithm with an accuracy of 95.74. SMO-SVM performance is high because it is an algorithm that reduces computational time by decomposing the quadratic programming (QP) problem that arises during the training of support vector machines (SVM), has good convergence for optimal solutions, and is memory-efficient (Flake & Lawrence, 2002; Gu et al., 2021).

The focus of the classification differs from what exists in the literature. The studies by Kuadey et al. (2022), Alshurideh et al. (2023), and Almaiah et al. (2021) examined the hypothesis of variables within the TAM and UTAUT models using machine learning; however, our study aims to employ a classification algorithm to forecast the cluster of new students. As shown in Figure 8, the cluster member groupings and variations present a pattern where classification algorithms in predicting the cluster of new students will alleviate the difficulties in applying the same pedagogical methodologies when students' data is updated.

Finally, the study used a chi-square test to estimate feature relevance on the dataset. Figure 12 depicts the results, highlighting the most influential features based on their rank during the classification algorithm's design.

CONCLUSION, LIMITATIONS, AND FUTURE WORK

The technology acceptance model (TAM) has been used widely in literature to understand how people accept and adopt new technologies. Applying this model has improved performance, efficiency, and convenience in a variety of sectors, including education. Despite extensive investigations on TAM in education, the utilisation of machine learning within TAM has been limited. This study employed machine learning within the technology acceptance model (TAM) and examined the patterns identified by clustering, correlation heatmap, and classification techniques. The correlation heatmap based on the Pearson correlation coefficient (PCC) reveals the extent of correlation among the variables in the TAM. The application of machine learning to the dataset from the University of Education, Winneba, Ghana, on students' actual usage of m-LMS reveals an unreliable correlation between attitude towards using (ATU) and actual system use (AU). This implies that even though students' desire to use m-LMS, they are not actually using it. It means that there are challenges surrounding the actual usage of m-LMS at the University of Education, Winneba. The machine learning study further clustered the students, aiming to provide instructors with pedagogical solutions to help students accept and use m-LMS for teaching and learning. The cluster type and behaviour patterns will require Tailored Solutions for Each Group.

STUDY LIMITATION

Although the research uncovered intriguing trends, there were minor setbacks. The first limitation is the use of convenience sampling. The limited representativeness of the sampling technique prevents the generalization of the research. Second, the data size is limited and cannot be used to generalise conclusions across the university regarding m-LMS. Third, the external factors in TAM that could trigger cognitive responses, PEOU, and PU, were not investigated. Lastly, the number of features investigated can be increased. The restriction on the number of features in the study can impact the performance of the machine learning algorithms.

FUTURE WORK

Subsequent research will broaden the data on m-LMS to include the majority of tertiary institutions in Ghana and further inculcate external variables for TAM analysis. The data will be indicative, allowing for the generalisation of inferences regarding national policy direction on m-LMS for education.

The investigation will also compare supervised learning algorithms to deep learning methods to determine the most dominant classifiers.

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