International Journal of Management and Marketing Systems
ISSN: 2384-537X, Volume 13, Issue 9, (May, 2023) pages 94 - 112
DOI: 272614566711396
www.arcnjournals.org

Design of a Personalized Learning Management System: Enhancing Student Learning Preferences

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Abstract: *The rapid expansion of high-speed network connectivity has brought about a significant transformation in multimedia experiences, prompting an increasing demand for e-learning as a complementary component to traditional classroom education. This thesis introduces a novel clustering method specifically tailored for user-centric functionality within LMS, leveraging the advancements in high-speed network connectivity. The proposed methodology employs a simulation-based approach to investigate its effectiveness. To ensure a focused research direction, a set of hypotheses is formulated based on the research objectives, guiding the investigation process. The study adopts the Simple K-Means algorithm as the fundamental clustering technique, while systematically configuring various parameters to drive the experimental process. Moreover, the thesis presents a postulated data preprocessing mechanism designed to cleanse and refine the data, ensuring access to high-quality datasets. Additionally, a modified user-centric framework is proposed to facilitate the implementation and serve as a comprehensive guide for future researchers. The research findings demonstrate the efficacy of the data preprocessing mechanism in accessing the appropriate datasets and highlight the potential of the modified user-centric framework for implementation in real-world LMS environments. Furthermore, the utilization of K-means clustering within learning management systems enables the effective grouping of learners with similar learning preferences, thereby resulting in improved learning outcomes. For future investigations, it is recommended to explore the integration of multiple clustering techniques to further enhance the clustering performance within LMS. Additionally, obtaining a dataset from the immediate environment of the study can provide valuable insights and strengthen the generalizability of the findings.*

Keywords: *e-learning, Learning Management Systems (LMS), clustering method, user-centric functionality, simulation methodology, data preprocessing mechanism, Simple K-Means algorithm, learning preferences, improved learning outcomes.*

INTRODUCTION

In the fast-paced twenty-first century, individuals strive to accomplish a significant amount of work efficiently. This trend is particularly evident in the manufacturing industry, where new and enhanced automobiles and mobile phones are introduced frequently, rendering previous models quickly outdated. Similarly, the education sector is also affected by this rapid progress, as it constantly seeks to adapt and provide diverse learning methods that cater to the unique needs of different student groups within the education system. (Abbad, 2021).
Since the late 1990s, the rapid advancement of technology has significantly transformed the

methods of teaching and learning in educational institutions (Pishva et al., 2020). E-learning, which relies on technology, refers to the utilization of the internet and other essential technological tools to create educational materials, instruct learners, and administer courses within an organization (Andersson et al., 2020).

The Internet has emerged as a crucial avenue for accessing research and learning resources, enabling both teachers and students to share and acquire information effectively (Al-adwan, 2020). In the field of education, e-learning platforms, also referred to as Learning Management Systems (LMSs), are web-based software that facilitate instructors in managing various aspects of their courses, such as distributing materials, assigning tasks, and facilitating communication (Bradley, 2021). According to Stodel (2020), the key factors that contribute to the immense potential of e-learning as an educational technology are service, cost, quality, and speed. Evidently, e-learning enables higher education students to pursue their education while simultaneously pursuing personal goals and maintaining their careers, without the need for adherence to strict schedules and This empowerment allows them to acquire education on their own terms.

In present times, Learning Management Systems (LMSs) have become a crucial element within the educational systems of the majority of universities. Furthermore, there is growing interest in adopting hybrid approaches that combine both in-person and online activities (Pishva, 2020). The concept of LMS originates from Integrated Learning System (ILS), which encompasses features that go beyond instructional content, including management and tracking capabilities, personalized instruction, and seamless integration throughout the system (Vaughan, 2020). Jostens Learning coined the term Integrated Learning System (ILS), while the initial use of Learning Management System (LMS) referred specifically to the management component of the PLATO K-12 learning system. Originally, LMS was independent of courseware and devoid of specific content (Eke et al., 2020). However, LMS has evolved into a broad term encompassing a variety of systems that organize and facilitate access to online learning services for students, teachers, and administrators. These services typically include functions such as access control, provision of learning materials, communication tools, and the organization of user groups (Aldiab et al., 2019).

A learning management system (LMS) is a comprehensive collection of interactive web-based e-services embedded within a software application. Its purpose is to facilitate the administration, documentation, tracking, reporting, and delivery of e-learning courses (Petrov, 2020). Essentially, LMSs serve as tools for the process of teaching and learning, enabling the acquisition of new knowledge and skills. Clustering, on the other hand, is a machine learning technique that involves grouping data points together based on their similarities. In the realm of education, clustering is employed to categorize learners based on factors such as their learning behavior, performance, or preferences.

One of the primary impacts of clustering in a Learning Management System (LMS) is its positive influence on learner performance. By categorizing learners based on their similarities, the LMS can generate customized learning paths that address their individual needs, thereby enhancing learning outcomes. This effect was observed in a study conducted by Paredes-Valverde et al. (2018). It is important to note that an LMS is not designed to replace traditional classroom settings but rather serves as a supplementary tool by providing course content accessible both on-campus and online (Landry et al., 2021). While the potential benefits of incorporating an LMS alongside traditional lectures have been acknowledged and explored, there is still limited understanding regarding the reactions of students and teachers when utilizing an LMS in addition to traditional classroom instruction.

LMS data is characterized as complex and voluminous, containing numerous features. Extracting relevant data features for decision-making by administrators and students is not a straightforward task. Therefore, clustering such intricate data is necessary to provide users with personalized recommendations and preferences (Ramadan et al., 2020). However, it is crucial to acknowledge that clustering techniques can inadvertently create stereotypical assumptions about learners, potentially resulting in discrimination or bias.

For instance, if a clustering algorithm categorizes learners based on their gender, it may generate biased assumptions regarding each group's learning preferences, leading to unequal treatment or opportunities (Torres-Trevizo et al., 2021). Several proposals have been put forth regarding learning management systems. However, existing frameworks that integrate search, clustering, and classification primarily focus on intrusion detection (Bamakan et al., 2016). These frameworks will be adjusted and applied to this study.

This paper would be guided by the following specific objectives:

i. To propose a preprocessing mechanism for cleaning data for the proposed system.
ii. To conduct an analysis on the user centric functionality of learning Management system.
iii. To propose a modified user centric framework for learning management system.
iv. To evaluate the proposed system based on the existing benchmark for clustering.

LITERATURE REVIEW

Theoretical Framework

Octagonal Model of E-Learning

When it comes to characterizing learning activities that make use of tasks, resources, and supports, the Octagonal Model of e-Learning Design Model gives an intriguing viewpoint. These formal descriptions "would provide the means to more easily guide the instructional design process and will also provide some means for institutions to provide supports and structures for teachers who wish to employ them," claim Khan et al. in Khan et al., (2021). Based on this, it could be said that the characteristics of this model are firmly rooted in the learning science perspective. It was used to explore strategies for formalizing the nature and scope of various learning designs using ICTs.

A thorough examination of all the factors and stakeholders must be taken into account from a system viewpoint point of view. This model is based on the octagonal structure for the e-learning system, which according to Khan (2021) also is grouped in the three major domains including its factors, in addition to offering comprehensive view on the relevant factors in the e-learning systems that can be used as measuring variables for e-learning effects and implementation.

Figure 2.2: Octagonal model of e-learning (Khan, 2021).

As can be seen, this model depicts 8 aspects that must to be taken into account while developing an e-learning system. This paradigm for e-learning design is seen to be particularly suited because these elements cover all area of e-learning. It is crucial to list every element that might affect how effective e-learning is. These elements are divided into three primary categories: managerial, technical, and educational. Additionally, each of the elements can be broken down into a number of difficulties that must be resolved. The pedagogical, ethical, and assessment aspects of education make up the educational realm. Technology and interface design aspects make up the technical domain. Additionally, institutional, resource-supporting, and managerial components make up the organizational domain.

Conceptualization

Learning

Learning refers to the process of acquiring new knowledge, modifying or strengthening existing knowledge, developing new behaviors and skills, adopting new values, or forming preferences. This process can involve the synthesis of various types of information (Fares et al., 2011). Human learning can take place within the context of education, personal growth, formal schooling, or training. It is often directed towards achieving specific goals and can be facilitated by motivation (Andersson et al., 2020). As described by Johnson and Johnson (2021), learning refers to the process of gaining new comprehension, knowledge, behaviors, skills, values, attitudes, and preferences. This capacity to learn is observed in humans, animals, and even some machines, with evidence suggesting that certain plants also exhibit some form of learning. Based on the given definition, it can be inferred that learning involves acquiring knowledge or skills through study, experience, or instruction. The study of how learning takes place falls within the domains of educational psychology, neuropsychology, learning theory, and pedagogy.

E-Learning

E-learning refers to the process of education that takes place over the Internet, a network, or on a standalone computer. It encompasses various applications and methods, such as web-based learning, computer-based learning, virtual classrooms, and digital collaboration (Kozma, 2020). E-learning involves the delivery of content through different mediums, including the Internet, intranet/extranet, audio or video tapes, satellite TV, and CD-ROM. Initially referred to as "Internet-Based Training" and later as "Web-Based Training," these terms are still used today, along with various other variations of E-learning (Kumar, 2020).

E-learning goes beyond mere training and instruction, as it also focuses on personalized learning experiences for individuals. Pishva *et al.* (2020) identified six key objectives in e-learning programs. These include building confidence and skills among practitioners, providing learners with access and choice, utilizing flexible and customizable systems and tools, establishing cost-effective technical infrastructures, implementing responsive e-learning policies and processes, and using e-learning to expand participation and offer flexible opportunities that support work-based learning within institutions.

Learning Management System

A learning management system (LMS), alternatively referred to as a course management system (CMS) or virtual learning environment (VLE), is a web-based software that facilitates the delivery, tracking, and administration of education and training. It encompasses functionalities for distributing courses online and fostering collaboration through the Internet (Johnson and Johnson, 2021). In the present era, learning management systems (LMSs) have become highly essential in the field of education (Kartha et al., 2021). Whether it is distance education or traditional classroom-based learning, LMSs are now widely adopted by universities to enhance the learning and teaching experience (Eke et al., 2021). For instance, as of 2005, around 95% of higher education institutions in the UK were utilizing course management systems. However, due to cost concerns, there is a growing trend of organizations transitioning to open source LMSs (Gulbahar et al., 2020).

As stated by Johnson and Johnson (2021), the benefits for trainers and organizations in utilizing e-learning include cost reduction, achieved through the elimination of expenses associated with instructor salaries, meeting room rentals, and student travel, lodging, and meals. Moreover, employees can save time by participating in e-learning without needing to be away from their job for extended periods. Another advantage is the ability to ensure consistent content delivery through asynchronous, self-paced e-learning. Expert knowledge is made accessible to all students, who can access it at any time. Additionally, proof of completion and certification, crucial aspects of training initiatives, can be automated in the e-learning environment.

Personalized Learning Experiences

Clustering is a technique that involves grouping data points together based on their similarities. In the context of Learning Management Systems (LMS), clustering can be utilized to group learners based on various factors such as their learning activities, interests, or preferences. By organizing learners into clusters, LMS can provide personalized learning experiences that cater to the specific needs of each cluster. For example, if a cluster of learners shares a common interest in a particular topic, the LMS can recommend relevant courses, activities, and assessments to them.

The impact of clustering on personalized learning experiences within LMS has been investigated in several studies. Wang et al. (2020) proposed a clustering-based framework that delivers personalized and targeted learning recommendations to learners based on their assigned clusters. This approach enables the provision of learning experiences that are specifically tailored to meet the individual needs and preferences of learners. Similarly, Adel et al. (2021) conducted a study that demonstrated how clustering can identify at-risk learners by analyzing their performance patterns. This early identification allows for timely intervention and the provision of personalized support to help these learners succeed.

METHODOLOGY

Framework

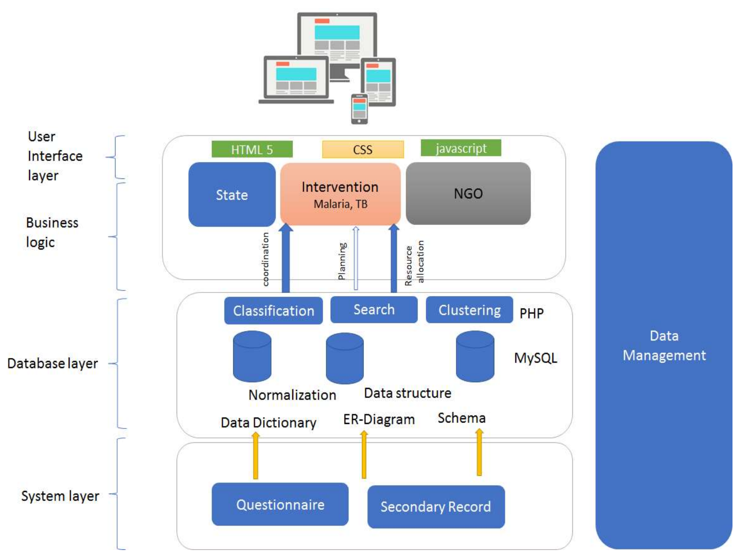

Figure 3.1:Existing framework by (Bamakan et al. 2021)

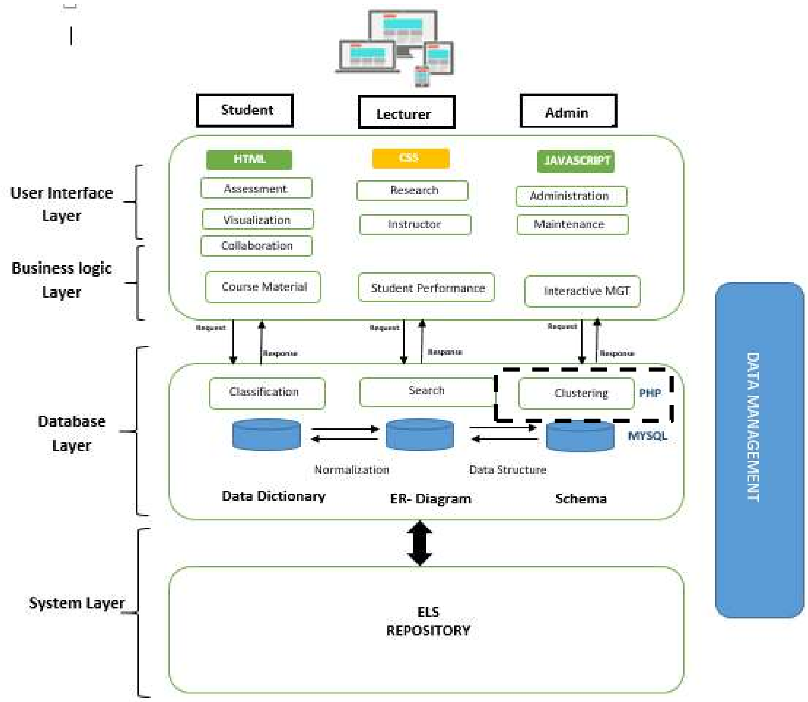

Figure 1: Proposed framework adapted from (Bamakan et al. 2021)

The Modified Framework

There exist numerous proposal on e-learning However, existing frameworks incorporating search, clustering and classification mainly target intrusion detection (Bamakan et al. 2021), which was used in an intrusion detection framework based on MCLP/SVM, in which he propose an effective intrusion detection framework by using a new adaptive, robust, precise optimization method, namely, time- varying chaos particle swarm optimization (TVCPSO) to simultaneously do parameter setting and feature selection for multiple criteria linear programming (MCLP) and support vector machine (SVM).

The application of intelligent methods allows systems to incorporate personalization features and tailor them to meet individual student requirements. By considering each user's preferences, multiple versions of teaching paths and materials can be created. To streamline the recommendations without losing personalization, learners can be divided into groups based on similar preferences. In the proposed architecture, the teaching path and layout are adjusted for groups of students with similar preferences using clustering techniques.

Learner models are based on dominant learning style dimensions, which reflect students' focus on different types of information and their performance in the educational process. By clustering students based on their learning styles and preferences, appropriate teaching paths can be assigned to groups of students with similar preferences. The proposed system allows for the adjustment of learning paths and layouts according to individual student preferences, considering their dominant learning styles and usability requirements.

During the pre-processing phase, a database of learning styles and usability preferences is created for a sample group of students. Using unsupervised classification, students are divided into groups with distinct preferences. Teaching materials and information content can be adjusted to cater to the needs of each group, enabling the creation of different learning paths. When a new student joins, their learning style and usability choices are recorded, and they are assigned to the appropriate group, receiving personalized learning materials and content.

This personalized approach allows for the creation of individual learning paths and modifications to teaching materials and their presentation methods for student groups with different preferences. However, the personal content remains static for each student during a course, although it may change when starting a new one.

Experiment Setup

The research choose simulation experiment to test the various ideas proposed. The experiment will comprise of clustering the LMS web log dataset in to clusters, to enable grouping of student into similar learning preferences. A simple K-means algorithm was considered, a web log data from Moodle was used. A total 150 and 100 dataset items are available in the dataset covering differing aspect of user weblog on Moodle learning management system (Stavros, 2021)., and the implementation part will involve encoding the dataset into a WEKA simulation software to conduct the experiment. The Sum of the error will be used to perform the similarity ratio of the experiment to determine the similarity index within the cluster.

The experiment will use a publicly available dataset of Moodle weblogs, consisting of 150 and 100 dataset items that cover various aspects of user weblogs on the Moodle learning management system. For the k-means algorithm, the number of clusters and clustering validity will be determined using the Pham (2021) table for select K-value in a dataset.

K-means algorithm for learning management systems (KM)

The algorithm tries to minimize the variance functions within each cluster and maximizing variance between clusters. Initially, in order to normalize the dataset records, we calculate the variance and the mean values for each record. This would represent the x value (mean) and y value (variance) for each dataset record, respectively. Based on this generated data, K-means algorithm is used for clustering such data. By default, k-means will minimize the variance and the mean values within each cluster.

The algorithm steps could be summarized as follows:

i. Step 1: The dataset D is divided into a number of sets S. S may depend on the number of distributed machines or number of threads to be used.
ii. Step 2: x value (mean) and y value (variance) are computed for each dataset record.

iii. Step 3: K-means clustering is applied to each set **s** ∈ ***S***. K is selected either heuristically or based on the number of records in each set.

iv. Step 4: At the global optimizers, Pareto optimality is applied to the clusters' centroids and non-dominated centroids.

v. Step 5: for non-dominated clusters, the distance between a point x and the cluster center is computed as well as the Silhouette scores between x and the nearest cluster center. Then, the K-means algorithm is used to re-cluster those points.

vi. Step 6: A window W is used to extract the most effective clusters based on the required points, e.g. LMS questions. Pareto optimality could be applied once more for better results.

RESULT PRESENTATION AND DISCUSSION

Experiment Setup

Summary of Parameters encoded on WEKA

The table 5 & 6, below shows the summary of the dataset encoded on weka simulation software, the relation name refer to the name of the file, the dataset has 150 and 100 instance, the dataset also have 6 attribute, the sum of the weight of the entire dataset is 150 & 100, while the simple Kmean with K=6 and K=1 value was used as the clustering method.

Table 4.1: Summary of 150 dataset parameter encoded on weka

Item	Value
Relation	Lms
Instance	150
Attribute	6
Sum of the weight	150
Missing	None
Clusterer	Simple Kmeans, K=6 and K=1

Table 4.2: Summary of 100 dataset parameter encoded on weka

Item	Value
Relation	Lms
Instance	100
Attribute	6
Sum of the weight	150
Missing	None
Clusterer	Simple Kmeans, K=6 and K=1

Source weka (2021)

Summary of statistical result on the Dataset.

From the statistical result shown on the table 7 below, the minimum and maximum value of the dataset set is 1 and 150, the mean of the dataset is 43.445 and the standard deviation for the dataset is 17.698 of the dataset while the cluster sum of the squared errors is 17.697.

Table 4.3: Summary of the statistical result from the dataset

Statistic	Value
Minimum	1
Maximum	150
Mean	75.5
Standard Deviation	43.445
Cluster sum of squared errors	17.697
Time taken to build Model full Training data	0.08 seconds
Num cluster	6

Source weka (2021)

Clustering Results

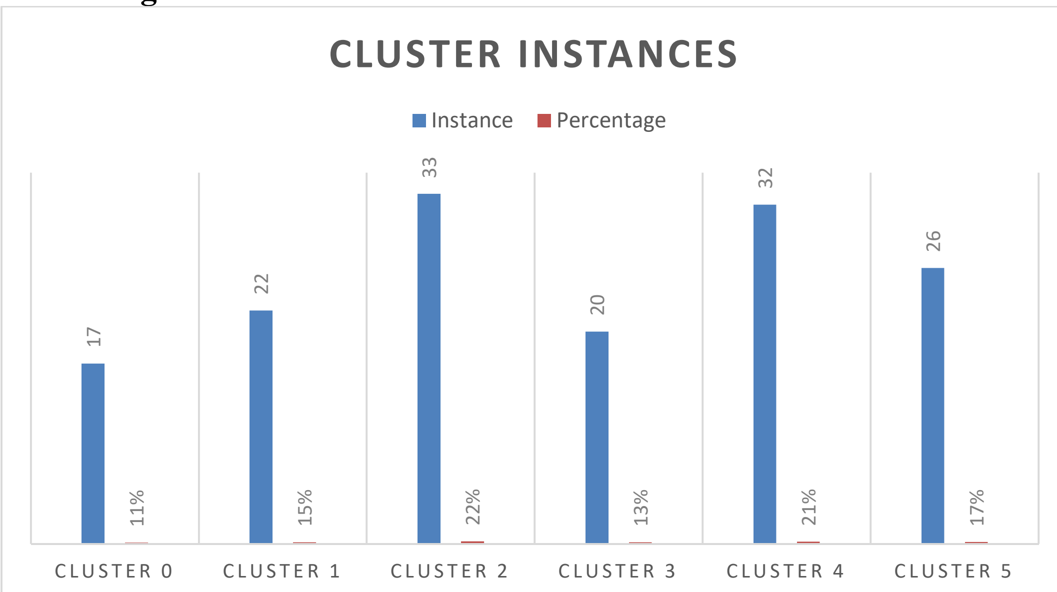

Figure 2. Cluster instances

From the Chart 1 above, the cluster 0 have 17 clustered data representing 11%, cluster 1 have 22 clustered data representing 15%, cluster 2 have 33 clustered data representing 22%, cluster 3 have 20 clustered data representing 13%, cluster 4 have 32 clustered data representing 21% while cluster 5 have 26 clustered data representing 17% of the dataset respectively with sum of the square error of 17.697 as the distance between the clusters.

Summary of the statistical result from the dataset

The table 8 below shows the summary of statistical result from the 150 weighted dataset with the minimum and maximum value of 1 and 150, mean of 75.5, standard deviation of 43.445, cluster sum of squared error of 49.09 while the number of cluster was 1.

Table 4.4: Summary of the statistical result from the 150 weighted dataset

Statistic	Value
Minimum	1
Maximum	150
Mean	75.5
Standard Deviation	43.445
Cluster sum of squared errors	49.09
Time taken to build Model full Training data	0.01 seconds
Num cluster	1

Source weka (2021)

Summary of statistical result on the Dataset for the 100 Instance.

From the statistical result shown on the table 5 below, the minimum and maximum value of the dataset set is 1 and 100, the mean of the dataset is 50.5 and the standard deviation for the dataset is 29.011 of the dataset while the cluster sum of the squared errors is 14.028.

Table 4.5: Summary of the statistical result from the dataset

Statistic	Value
Minimum	1
Maximum	100
Mean	50.5
Standard Deviation	29.011
Cluster sum of squared errors	14.028
Time taken to build Model full Training data	0.01 seconds
Num cluster	6

Source weka (2021)

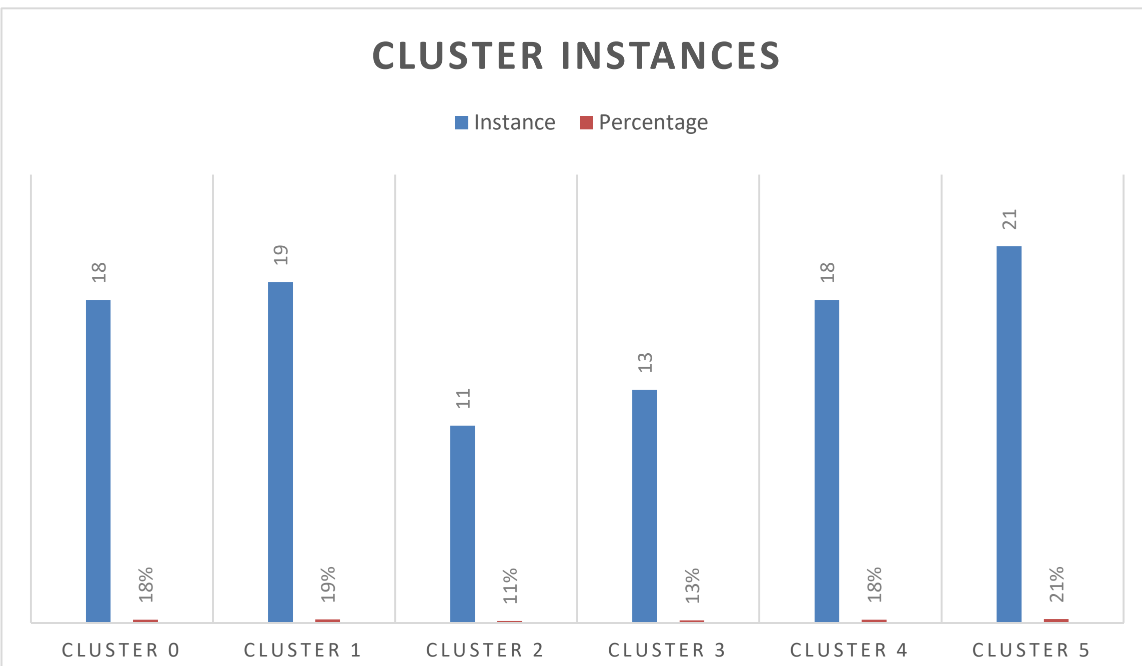

Figure 3: Showing the 100 Clustered instances

From the Chart 1 above, the cluster 0 have 18 clustered data representing 18%, cluster 1 have 19 clustered data representing 19%, cluster 2 have 11 clustered data representing 11%, cluster 3 have 13 clustered data representing 13%, cluster 4 have 18 clustered data representing 18% while cluster 5 have 21 clustered data representing 21% of the dataset respectively.

Summary of statistical result on the Dataset for the 100 Instance.

From the statistical result shown on the table 5 below, the minimum and maximum value of the dataset set is 1 and 100, the mean of the dataset is 50.5 and the standard deviation for the dataset is 29.011 of the dataset while the cluster sum of the squared errors is 39.934.

Table 4.6: Summary of the statistical result from the dataset

Statistic	Value
Minimum	1
Maximum	100
Mean	50.5
Standard Deviation	29.011
Cluster sum of squared errors	39.934
Time taken to build Model full Training data	0.00 seconds
Num cluster	1

Source weka (2021)

Similarity index between Non-Clustered and Clustered instances

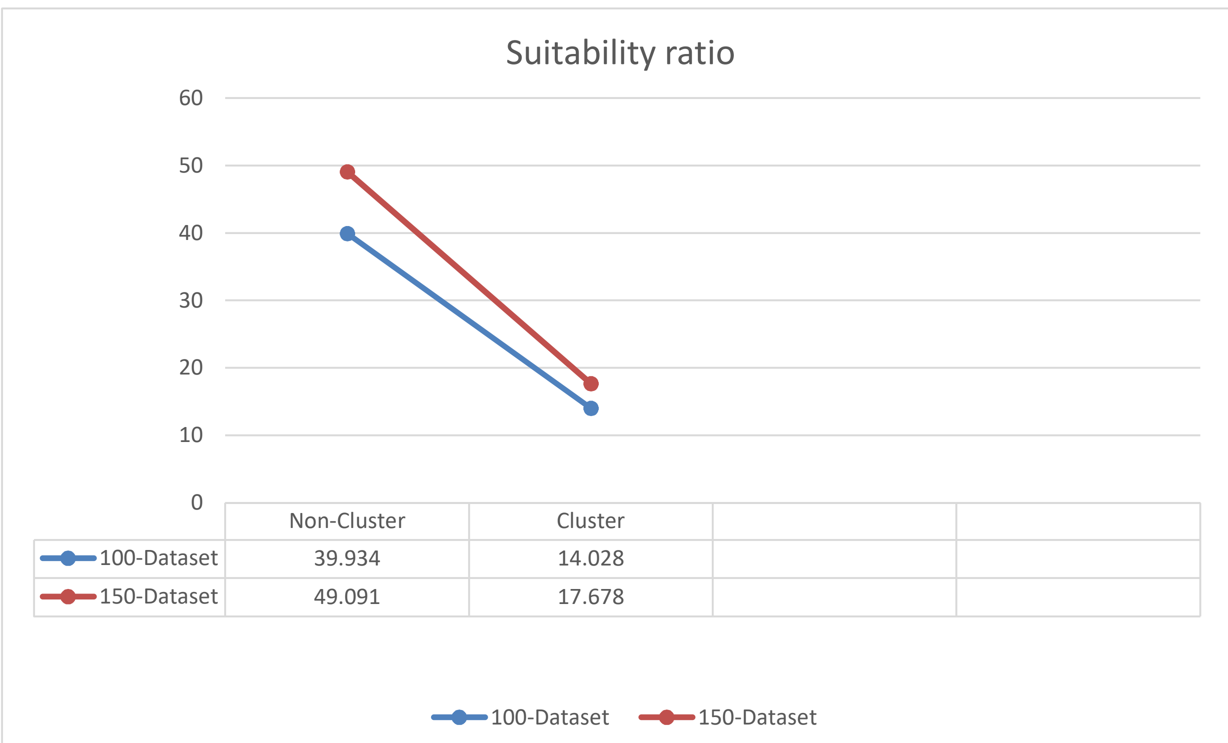

Figure 4: Similarity index between Non-Clustered and Clustered instances

From the experiment, the chart above combined the Two (2) various dataset of different weight to observe the similarity index of each of the dataset on the 150 dataset was classified into two namely the clustered and the none-clustered, the clustered dataset has 6 clusters having 17.679 similarity index while the non-clustered instance have 49.09 similarity index within the instance of it cluster. The 100 weighted dataset experiment was classified into two part with are the clustered and the non-clustered the clustered dataset. The clustered was dataset has 6 clustered and 14.028 as the similarity index within the cluster compared to the non-clustered which has a high 39.934 similarity index within it instances. The cart above provide wide indication on the 2 dataset and the similarity index and was observed that the clustered instances has a low similarity index compared to the non-clustered instances meaning that the clustered instance will be used in delivering the right learning content to users with similar learning preferences.

Cluster Visualization

The students were organized into clusters using the simple K-means Clustering method, which reveals the relationships between the students. The clusters were visualized, with vectors representing the connections between students. To be connected, students needed to have similar characteristics in terms of site visits. The clusters were created based on the attributes and classes of the students, as encoded in the initial stage. The colors used in the visualization indicate the variations among the clusters. The Figures below show the visualization of the results using the variables X (interest) and Y (interest). The blue, red, and green points represent different classes and clusters. The metrics used in the analysis contain valuable information about the courses and can differentiate them into distinct groups.

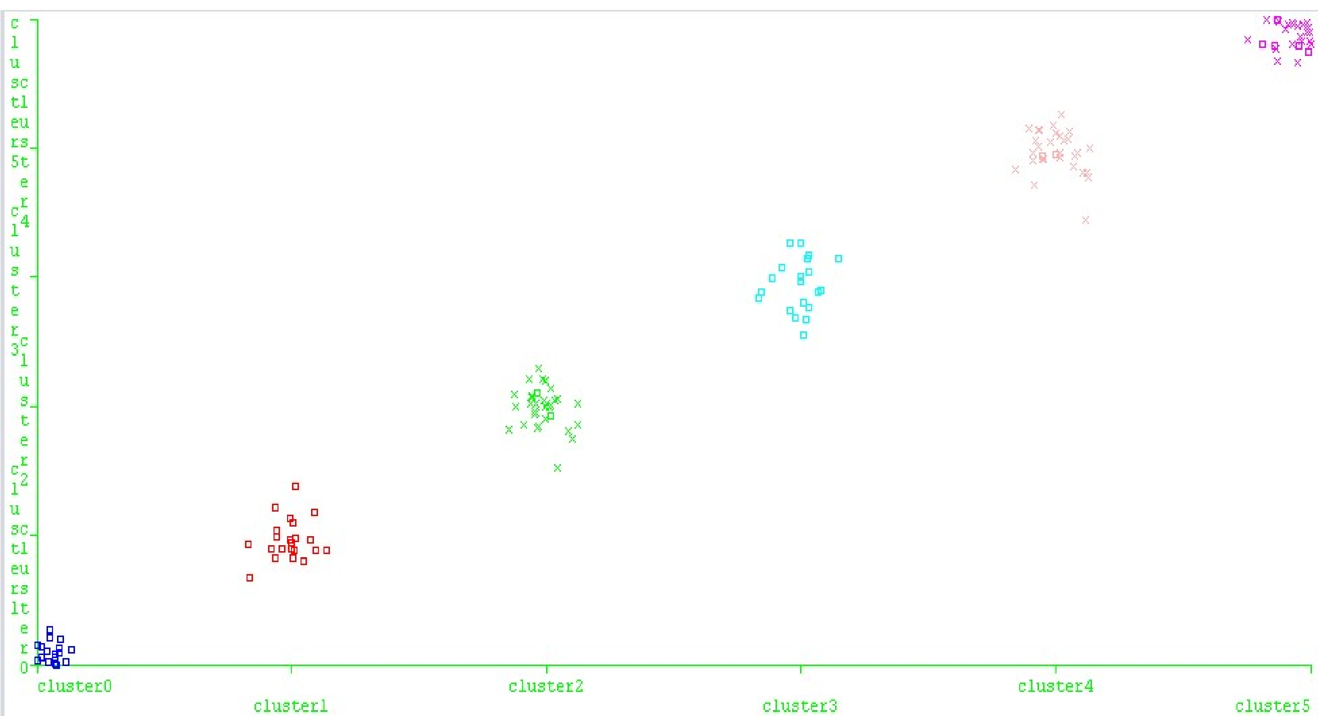

Figure 5: Clustering: Visualized simulated data based on the 6 clusters with 50% Jitter

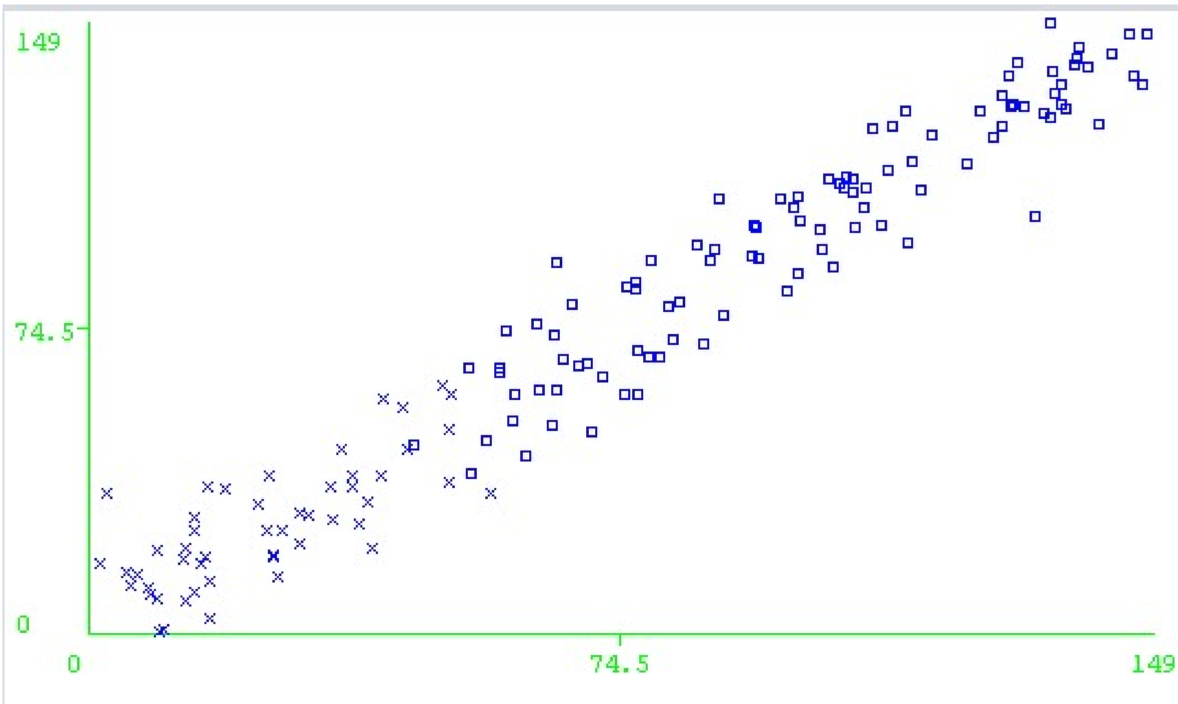

Figure 6: Visualization based on Non-clustered instance with 50% jitter.

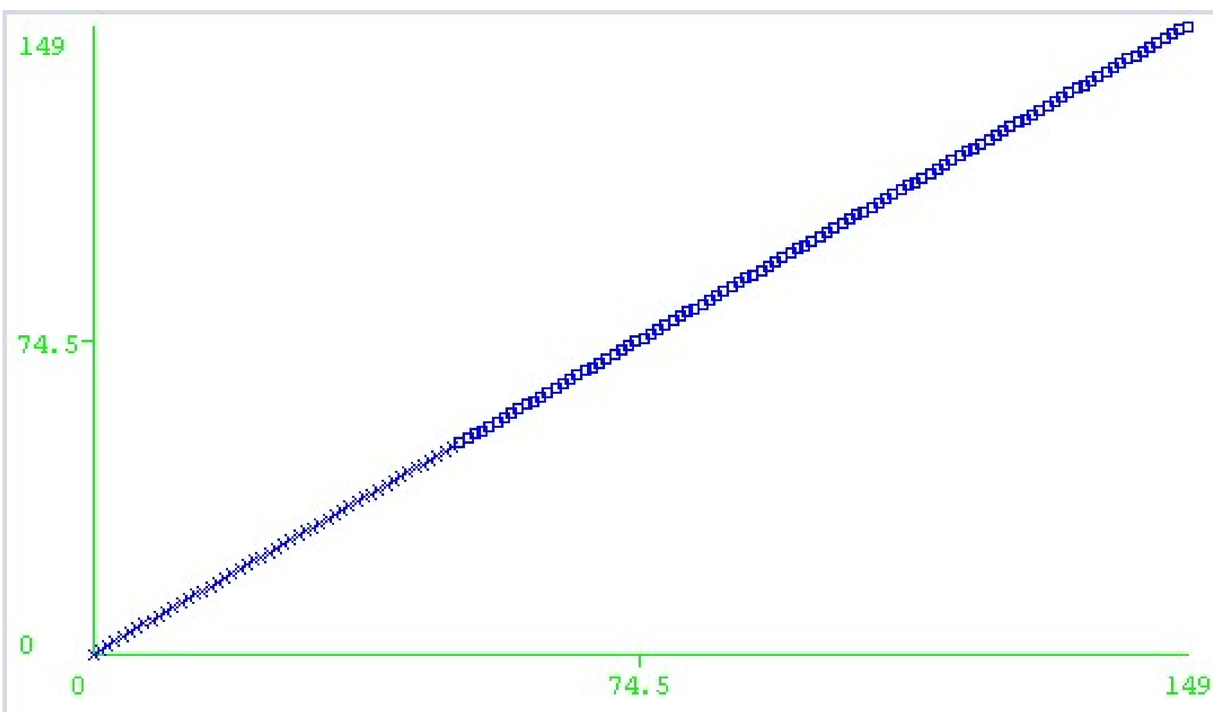

Figure 7.Visualization based on the Non-Clustered instance with 0% Jitter

Discussion of Findings

In this study, the researchers aimed to group students with similar learning preferences using Moodle log data. They employed the Simple K-means algorithm in WEKA to partition the dataset into distinct clusters. Two datasets were used: one with 150 weighted instances and another with 100 weighted instances.

For the 150-instance dataset, the experiment was conducted in two phases: clustered and non-clustered. The clustered dataset had a sum of weights of 150, a mean of 75.5, and a standard deviation of 43.45. By applying K-means with a value of 6, 6 clusters were formed. The distribution of instances within each cluster varied, with cluster sizes ranging from 11% to 22%. The sum of square error for the clustered dataset was 17.697, indicating similarity within the clusters. In contrast, the non-clustered dataset exhibited a higher sum of square error of 49.09, suggesting dissimilarity.

In the second experiment with the 100-weight dataset, K-means was again employed with K=6. The dataset had a mean of 50.5 and a standard deviation of 29.011. The resulting clusters had varying sizes, ranging from 11% to 21%. The low similarity index within the clusters was 14.028, and the non-clustered dataset had a higher sum of square error (39.934), indicating dissimilarity.

The researchers visually represented the dissimilarity within the clustered and non-clustered datasets in Figure 4.3. The figure showed that the non-clustered dataset had a higher sum of square error, while the clustered dataset exhibited a lower sum of square error, indicating similarity within the clusters. The visualization of the results using interest as the X and Y axes demonstrated that the metrics used contain valuable information about the students, allowing for differentiation into distinct groups.

This research provides evidence that clustering can effectively group students based on their learning preferences, reducing dissimilarity within the clusters. The study emphasizes the significance of metrics in distinguishing students and highlights the importance of visualizations in analyzing the results.

Result Validation

In this research, K-means clustering was employed to identify similar learner preferences among students (Wang et al., 2020). The experiment consisted of two phases with two datasets and was classified into four phases, each containing two subphases. The validation of the results was based on the objectives, as outlined by the researchers.

The existing learning management system (LMS) was analyzed through a literature review. Wang et al. (2020) emphasized the need for a user-centric approach in LMS that utilizes clustering techniques to group learners based on their characteristics and preferences. As the number of online learners in LMS increases, it becomes challenging to provide personalized learning experiences that cater to their diverse needs. Thus, there is a demand for an effective user-centric approach that utilizes clustering techniques to group learners based on their characteristics, preferences, and behavior, in order to provide personalized and targeted learning experiences.

LMS data is considered complex and voluminous, making it challenging to extract meaningful features for decision-making (Ramadan et al., 2020). Therefore, clustering is required to group such complex data and provide users with preferences. However, it is important to be cautious about the potential creation of stereotypical assumptions or biases through clustering techniques, as they can lead to discrimination or unequal treatment (Torres-Trevizo et al., 2021).

The proposed modified framework, based on the work of Bamakan et al. (2019), focused on clustering to enhance learning preferences by dividing learners into groups with similar preferences. Preprocessing of web log data involved filtering and computation of values using established metrics. The index value computation for the UniquePCSession and enrichment metrics were adapted from the framework proposed by Kazanidis et al. (2021), while the disappointment and interest metrics were introduced by Binali et al. (2021) and Valsamidis et al. (2010a) respectively.

Although the K-means algorithm is popular for data clustering, it requires the specification of the number of clusters (K) before application. The selection of the number of clusters and the assessment of cluster validity for the K-means algorithm were done using the table provided by Pham (2021) indicating the number of clusters used in different studies. Milos et al. (2022) applied K-means clustering with K=6 to group students based on their cognitive learning style, demonstrating positive results in improving cognitive learning experience. Similarly, Mohammed (2019) employed a simple K-means clustering algorithm with K=4 to improve graduate student performance, indicating positive results with a low sum of square error.

Several studies have demonstrated the effectiveness of K-means clustering in grouping learners based on similar learning preferences. Dake and Gyimah (2019) used K-means clustering to determine learners' typologies for project-based learning, while Herlina et al. (2021) implemented K-means clustering to classify student learning activities in an e-learning model. Both studies highlighted the success of K-means clustering in grouping students with similar learning preferences. The performance of the proposed method was evaluated by examining the quality of obtained clusters, considering student learning styles. The number of instances with different preferences assigned to the same clusters and the sum of square error were used as measures of quality, similarity index, and distance from different points to the clusters.

CONCLUSION AND RECOMMENDATIONS

The aim of this study was to address the problem of the user centric functionality in learning management system, objectives where proposed to address the problem by clustering students with the aim of grouping students exhibiting similar learning preferences. A framework was adapted with main focus on the database layer with specific interest in clustering students into individual learning preferences with the teaching materials as well as the information content adjusted to the needs of every group with different learning path also created through this means. A number of proposal existed on learning management system however, a framework was adapted with main focus on clustering students into individual learning preferences enabling teaching materials as well as information content to be adjusted to the needs of every group with similar learning style. A preprocessing mechanism was proposed to enable cleaning of that obtained from the weblog that contains noise such as missing values as well as the value computation metrics.

The preprocessing mechanism filter the data and the value computation metrics was used on the filtered data to provide a valid results. The evaluation of the result was done based on exiting bench mark for clustering, the Sum of the square error was used to measure the performance of the clusters and similarity index within the clusters, which measure the distance from each point of the cluster to the centroids. The sum of square error has also been used by authors in there clustering validity. While existing research has failed to address the issue of user centric functionality with core focus on providing learning preference and user weblog on their LMS design, this research has filled the gap by integrating user activity log to the learning management system.

The study recommended that similar experiment can be conducted using a dataset from the immediate environment of the study. Dataset from public Moodle LMS are traditionally unclean and should be subject to appropriate cleaning and value computation matric during the data preprocessing stage as I have proposed. A combination of multiply clustering algorithm such as X-means and Density based clustering can be employed to archive better result.

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