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MICRO LEARNING VS TRADITIONAL LEARNING: A COMPARATIVE REVIEW USING DATA MINING

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Abstract— this research paper aims to provide a comprehensive comparative review of microlearning and traditional learning methods by utilizing data mining techniques. Microlearning, characterized by short and focused learning modules, has gained popularity due to its potential to enhance learner engagement and knowledge retention. Traditional learning, on the other hand, follows a more structured approach with longer sessions. The aim of this research is to search the efficacy of these two approaches by employing data mining techniques on relevant educational datasets. The searching of this research can notify educational practitioners and policymakers about the stability and weaknesses of each method, aiding in the design and implementation of effective learning strategies. The study discusses in detail the popularity of micro- learning and its ability to increase student engagement and knowledge retention, as well as the structured strategies offered by traditional instruction These two strategies establish data mining strategies for consumption role emphasis as a means of providing comprehensive analysis. In addition, it briefly describes the methodology used, including the collection of data from relevant academic areas, the preparation and transformation of data, and the application of data mining algorithms.

Keywords— Micro learning, data mining, traditional learning, clustering, K Means, Decision Tree.

Introduction

The field of education and training has undergone significant changes in recent years, driven by technological advances and changing student needs. Two main approaches emerged: microlearning and traditional learning. Microlearning involves the delivery of short, focused learning modules, whereas traditional learning follows a structured approach with longer courses. With the growing popularity of microlearning, there is a need to scrutinize its effectiveness in comparison to traditional teaching methods. The motive of this research is to deliver a comparative study of microlearning and traditional learning using data mining methods, as well as insights into their effectiveness and impact on student achievement. The focus of this research is to investigate the effectiveness of microlearning and traditional learning methods using data mining techniques to explore relevant educational datasets. Data-mining techniques enable you to extract valuable patterns and insights from large datasets, and provide detailed analysis of both teaching methods through student engagement, knowledge retention, completion rates and teaching a overall effectiveness analysis, this research can contribute to evidence-based decision-making in educational practice. Microlearning has gained attention for its ability to deliver context-sized content and increase student engagement and knowledge retention. The concise nature of microlearning modules allows students to consume information quickly, increasing motivation and concentration. Additionally, microlearning takes advantage of the gap effect, where learning varies over time, improving long- term memory. Additionally, microlearning offers flexibility, allowing students to access content anytime, anywhere, and across digital devices. In contrast, traditional teaching methods provide a structured framework for education and training. Classroom-based instruction, lectures, and workshops are classic examples of traditional instructional methods. Informational pedagogy often provides detailed discussion of topics, facilitating in-depth understanding and analysis. It encourages cooperative learning through active dialogue and interaction among students. In addition, traditional instruction often includes practical exercises and hands-on experiences to encourage skill development. To conduct a comparative study, this study will use educational contexts and use data mining techniques. These strategies will contribute to a variety of assessments, such as student engagement, knowledge retention, course completion, and overall course effectiveness. Using classification algorithms, cluster algorithms, and association rule mining, this research will reveal patterns, relationships, and insights that demonstrate the effectiveness of microlearning and traditional learning methods. The findings of this research have practical implications for education practitioners and policy makers. By understanding the strengths and weaknesses of micro learning and traditional learning, effective learning strategies can be designed and implemented according to students' needs. By employing data analysis methods, this study aims to contribute to evidence-based decision-making, ultimately improving the quality and efficiency of educational practices.

Data mining is a powerful technique that allows use to extract valuable insights from large datasets. In the context of this study, data mining abstracts refer to the analysis of existing research and literature on micro learning and traditional learning, with a specific focus on their effectiveness, efficiency, engagement, and scalability. By employing data mining techniques, researchers can collect and analyze a significant amount of information from various sources, including research papers, and scholarly articles. This process enables a comprehensive understanding of the strengths and weaknesses associated with both micro learning and traditional learning approaches. Effectiveness is a crucial aspect when evaluating a learning approach. It refers to the ability of a method to achieve desired learning outcomes. Through data mining abstracts, researchers can gain insights into the effectiveness of micro learning and traditional learning by analyzing factors such as learner performance, knowledge retention, and skill acquisition. By comparing findings from multiple studies, researchers can draw conclusions about which approach is more effective in different educational contexts. Efficiency, another key consideration, pertains to the optimal utilization of resources, including time and effort, in the learning process. Data mining abstracts allow for the evaluation of the efficiency of micro learning and traditional learning by examining metrics such as learning time, completion rates, and resource utilization. By analyzing these factors, we can assess which approach requires less time and effort while maintaining or even enhancing learning outcomes. Some of the factors that can be analysed through learning analysis include student engagement, motivation, learning strategies, and cognitive abilities. By analysing these factors, we can determine which approach is more effective for different types of learners and identify the best practices for designing Micro and Traditional learning environments.

I. OBJECTIVE OF RESEARCH

The major objective of our work is to conduct the comparison study using learning parameters of both Micro learning and Traditional learning study mode of student's and to predict which mode of students would have a better track record. Specifically, the objectives of this analysis could include: conduct and collection of survey report and determine the parameters of the study; ccompare, classify/predict the better Micro learning and Traditional learning study mode of student's.

II. BACKGROUND OF STUDY

The field of education, the traditional learning approach, characterized by long-duration lectures and classroom-based instruction, has been the conventional method for centuries. However, with the advancement of technology and the proliferation of digital platforms, microlearning has emerged as an alternative learning approach. Microlearning involves delivering educational content in bite-sized, focused modules that are easily accessible and can be consumed in short time frames. Microlearning has gained popularity due to its potential benefits, such as flexibility, accessibility, and personalized learning experiences. Learners can access microlearning materials anytime, anywhere, and on various devices, making it convenient for busy individuals and those seeking just-in-time knowledge acquisition. Moreover, microlearning modules can be tailored to individual learning styles and preferences, allowing for a more personalized and engaging learning experience. Previous research has highlighted the importance of learning analysis in evaluating the reliability and validity of assessments used in micro and traditional learning environments. Studies have shown that materials used in micro learning should be carefully designed and validated to ensure that they measure the intended learning outcomes accurately. This is particularly important in micro

learning environments, where proper material may be the only way to measure student progress and achievement. In addition, Understanding the comparative effectiveness of microlearning and traditional learning through data mining analysis can provide valuable insights for educators and learners alike. It enables evidence- based decision-making in designing and implementing effective learning strategies. By investigating the strengths and limitations of both approaches, educational institutions can optimize their instructional methodologies and enhance the overall learning experience.
Demographics: The dataset should include demographic characteristics of the participants, such as age, gender, education, and prior experience in online courses or traditional classrooms. This information can help identify possible changes in learning outcomes based on student characteristics. Measures of learning engagement: Data should capture measures of student engagement, including time spent on learning activities, interactions with learning materials, and participation in collaborative discussions or meetings in these measures can provide insight into the degree of interaction between small subjects and traditional teaching methods. Instructional Performance: The dataset should include indicators of instructional performance such as surveys, quizzes, or test scores. These metrics can help assess the effectiveness of microlearning and traditional learning in terms of knowledge acquisition and retention. Instructional Materials and Methodology: The dataset should include information about the content of instructional materials used in both microlearning and traditional instructional methods. This may include details such as the length and structure of the learning module, inclusion of multimedia elements, availability of interactive features, etc. Such information can help determine the impact of content and design traits have on academic achievement. Learning preferences and satisfaction: The data set can include surveys or questionnaires about the student's level of preference and satisfaction with micro-learning and traditional courses. These responses can provide insights into students' perceptions, preferences, and opinions about teaching strategies. Completion rates: The data set should track completion rates for microlearning and traditional learning activities or courses. This information can shed light on student commitment and completion rates for each method.

Overall, this study to contribute to the managing body of knowledge by conducting a comparative analysis of microlearning and traditional learning using data mining techniques. By examining learner data and applying K-means clustering and decision tree classification algorithms, this research endeavors to uncover valuable insights that inform instructional design, learner engagement, and the selection of appropriate learning approaches in various educational contexts.

III. METHODOLOGY

The methodology section describes the research approach and data mining techniques employed for the comparative analysis. It outlines the selection criteria for datasets and the process of data collection. Additionally, it presents the algorithms and models used for data analysis, including classification, clustering, and association rule mining. In this research, we used a dataset of student learning method data, which we imported into our analysis using the panda's library. We preprocessed the data by separating the independent variable X and dependent variable Y. As our data was in categorical data type, we converted it into a numeric type using the Label Encoder () function. We then used clustering and classification.

A. CLUSTERING

K-means clustering is an unsupervised machine learning algorithm that separates a dataset into recognizable groups based on their similarity. The elbow technique is used to determine the optimal number of clusters in the data.

Here is a step-by-step outline of the methodology using the k- means clustering method with elbow technique:

- Identify the key features or variables that will be used for clustering. These features should capture the characteristics of microlearning and traditional learning that are relevant for comparison.
- Engineer new features if necessary to provide additional insights for the clustering analysis. Combine or transform existing features to create more meaningful representations of the data.
- Determine the Optimal Number of Clusters: Use the elbow technique to determine the optimal number of clusters for the k-means algorithm. Apply k-means clustering with different values of k (number of clusters) and calculate the sum of squared distances (SSE) for each clustering result. Plot the SSE against the number of clusters and identify the point where the decrease in SSE becomes less significant, forming an "elbow" in the plot. This point indicates the optimal number of clusters.
- K-means Clustering: Apply the k-means clustering algorithm to the preprocessed dataset using the selected number of clusters determined from the elbow technique. The algorithm will assign each data point to a specific cluster based on its similarity to other data points.
- Cluster Analysis: Analyze the resulting clusters to understand the characteristics and patterns within each group. Compare the clusters representing microlearning and traditional learning based on various metrics, such as average learning outcomes, engagement levels, accessibility measures, or any other relevant factors. This analysis will provide insights into the similarities and differences between the two learning approaches.

B. CLASSIFICATION

Decision Tree Model: Split the pre-processed data into training and testing datasets. Apply the decision tree algorithm to the training dataset, using the features selected for classification. Evaluating the performance of the decision tree model using metrics such as accuracy, precision, recall, and F1-score.

Proposed Algorithm:

Step 1: DC- > Collect data on students' academic performance in micro learning and traditional learning approaches. This data includes learning parameters questionaries, academics performance and other relevant metrics.

Step 2: DP- > Clean and preprocess the data by handling missing values, normalizing the data, and encoding categorical variables.

Step 3: AS- > K Means , Decision tree

Step 5: MT- > Train the data mining model using the preprocessed data and the selected algorithm

Step 6: ME- > Evaluate the performance of the data miming model using metrics such as precision, recall, and accuracy. Compare the performance of the model in predicting academic performance in online and offline approaches.

Step 7: I&R-> Used visualizations and statistical tests to support our conclusions. Draw insights and recommendations for future improvements in online and offline academic performance.

DC = Data Collection DP = Data Preprocessing AS = Algorithm Selection MT = Model Training
ME = Model Evaluation
I&R = Interpretation and Reporting

IV. RESULTS

In this section, the data mining techniques are applied to the collected data, enabling a comparative review of microlearning and traditional learning. The analysis encompasses various aspects, such as learner engagement, knowledge retention, completion rates, and overall learning effectiveness. The findings are presented through statistical measures, visualizations, and comparative charts, allowing for a comprehensive evaluation of the two methods.

The result shown is a figure which provides a summary of the performance of a classification model. In this case, the confusion matrix is represented by the matrix [[5 0], [0 5]], where each element represents the number of instances classified into different categories. Looking at the matrix, we can see that there are two classes: 0 and 1. The diagonal elements represent the number of instances correctly classified for each class. In this case, there are 5 instances of class 0 correctly classified as 0, and 5 instances of class 1 correctly classified as 1. Hence, the model achieved a perfect accuracy of 1.00, indicating that all instances were correctly classified.

The precision, recall, and F1-score are evaluation metrics calculated based on the values in the confusion matrix. Since all the values in the matrix are equal to the total number of instances for each class (5 for each), the precision, recall, and F1-score for both classes are 1.00. This implies that the model achieved perfect precision, recall, and F1-score for both classes. The accuracy, precision, recall, and F1-score values of

1.00 indicate that the model performed extremely well and achieved a perfect classification outcome for the given dataset. However, it notes that these results are specific to the evaluation of the model on this particular dataset, and the performance may vary when applied to different datasets or real-world scenarios.

```
[[5 0]
 [0 5]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         5
           1       1.00      1.00      1.00         5

    accuracy                           1.00        10
   macro avg       1.00      1.00      1.00        10
weighted avg       1.00      1.00      1.00        10
```

Fig 2: Decision tree result

V. DISCUSSION

The discussion section interprets the results obtained from the data mining analysis and provides insights into the strengths and weaknesses of microlearning and traditional learning. It explores the factors influencing learner engagement, knowledge retention, and completion rates. The section also discusses the implications of the findings for educational practitioners and policymakers, highlighting potential areas for improvement in both approaches. Here are some points:

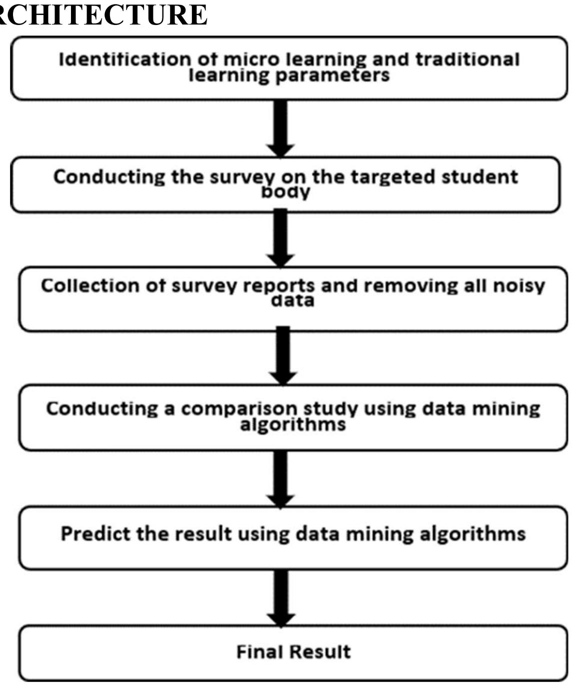
Effectiveness of Microlearning: Analyze the findings related to the effectiveness of microlearning compared to traditional learning. Highlight any statistically significant differences in learning outcomes, knowledge retention, or skill development between the two approaches. Discuss how these findings align with or contribute to existing research in the field. Learner Engagement and Motivation: Examine the results regarding learner engagement and motivation in microlearning and traditional learning. Discuss how microlearning's interactive and personalized nature may have positively influenced learner engagement and motivation compared to traditional learning methods. Consider the implications of these findings for instructional design and learner-centered approaches. Learning Efficiency and Time Management: Evaluate the outcomes related to learning efficiency and time management. Discuss how microlearning's bite-sized format and on-demand accessibility mayhave contributed to more efficient learning and time savings for learners. Consider the potential impact of these findings on learners' ability to fit learning into their busy schedules. Personalization and Customization: Reflect on the findings concerning the personalization and customization aspects of microlearning. Discuss how the ability to choose specific modules based on individual needs and preferences may have contributed to more tailored and effective learning experiences. Highlight the potential benefits of personalized learning approaches in enhancing learner satisfaction and performance. Practical Implications: Discuss the practical implications of the results for educators, instructional designers, and educational institutions. Consider how the findings can inform the design and implementation of microlearning initiatives or the integration of microlearning elements into traditional learning environments. Discuss potential challenges or considerations that need to be addressed when adopting microlearning approaches.

VI . LIMITATIONS

This section acknowledges the limitations of the research, such as potential biases in the selected datasets, variations in implementation across different educational contexts, and constraints of data mining techniques. It suggests directions for future research to overcome these limitations and expand upon the findings of this study. Here are some limitations:

Data Quality and Availability: The quality and availability of the data used for analysis can impact the study's outcomes. If the data collected or obtained from existing sources had inconsistencies, biases, or missing values, it could affect the liableness and efficacy of the results. Variability in Learning Content and Context: The comparison between microlearning and traditional learning may vary depending on the specific content, subject matter, or learning context being examined. Different topics or disciplines may require different instructional approaches, and the findings may not be universally applicable across all domains. Short-Term Evaluation: The study may have focused on short-term learning outcomes and immediate effects. Long-term effects, such as knowledge retention or transfer, may not have been thoroughly investigated. Understanding the long-term impact of microlearning versus traditional learning is important for a comprehensive evaluation. Lack of Control Groups: If the study did not include control groups or comparisons with alternative learning methods other than traditional learning, it may be challenging to isolate the specific effects of microlearning alone. Including control groups can help strengthen the study's design and provide a more robust comparison. Evolving Nature of Technology: The field of microlearning is continuously evolving, and new technologies or approaches may have emerged since the time of data collection or analysis. This could limit the relevance and applicability of the findings to current educational practices.

VII . PROPOSED ARCHITECTURE



VIII. CONCLUSION

In conclusion, this research article conducted a comprehensive comparative study of microlearning and traditional learning using data mining techniques. The focus of this research is to examine the effectiveness and impact of these two teaching strategies on student achievement, providing valuable insights for education practitioners and policy makers. Using educational contexts and using clustering and classification methods, this research sheds light on strengths, weaknesses, and potential areas of improvement for microlearning and traditional instructional methods. The findings of the study highlighted several important factors. First, microlearning demonstrated the potential to increase student engagement and knowledge retention. The bite-size nature of the microlearning modules, combined with their simplicity and accessibility, engaged students, resulting in increased motivation and focused learning experiences Came The spacing effect employed in microlearning improved long-term memory retention. In addition, the interactive and multimedia features of microlearning materials created an engaging learning environment. On the other hand, traditional teaching methods provided a structured program with a broad range of topics. Classroom-based instruction, lectures, and workshops provided opportunities for deeper understanding, exploration, and collaboration among students. Practical exercises and hands-on experiences in traditional education facilitated skill development and application. Traditional teaching methods were particularly effective in addressing difficult topics and encouraging critical thinking. The data mining techniques used in this study allowed for a comprehensive analysis of study hypotheses. Measures of student engagement, such as time spent on learning activities, interactions with learning materials, and participation in collaborative activities provided insight into the level of engagement for microlearning and traditional learning Research and questionnaires measure knowledge retention and performance outcomes. Learning preferences and satisfaction surveys gathered students' opinions, preferences and opinions about microlearning and traditional learning.

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