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Identifying Student Behaviour Patterns Based on LMS Data

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Abstract. In contemporary education, data analysis methods to establish patterns of student behaviour for subsequent optimization of the educational process are becoming increasingly relevant. This paper presents research aimed at identifying patterns of student behaviour based on the processing of data obtained from Learning Management Systems (LMS). The article examines data collection and analysis issues from LMS, including activity logs, grades, participation in forums, and other interactive elements. Additionally, methods such as statistical analysis and machine learning, applied to identify patterns of student behaviour, are discussed. The text describes the identified patterns of student behaviour in the electronic educational environment, which are subsequently linked to students' academic performance levels. The paper's concluding section presents the research findings and potential scenarios for their application.

Key Words: adaptive learning, machine learning, learning management systems, student behaviour patterns

1.INTRODUCTION

In the era of digitalisation of education, learning management systems (LMS) have become an integral part of the educational process, offering unique opportunities to collect and analyse student behaviour data. These data represent a rich source of information that can be used to optimise learning and improve educational outcomes [1]. One of the key findings in the study of student behaviour is the identification of various behaviour patterns, such as active participants, passive observers, engaged in discussions, lagging, and independent learners [2]. These behaviour patterns help to understand how students interact with the course material and each other and provide data regarding their educational preferences [3, 4].

Active participation in learning, especially in discussions and group projects, is closely linked to high academic achievement. It supports the idea that engagement and active interaction with the material of studied disciplines contribute to better assimilating knowledge and developing critical thinking [5]. In contrast, although passive observers have access to the same resources, they often show average or below-average results due to a lack of subjective activity and deep immersion in the material studied.

It is worth noting that students selecting certain sections of the course for in-depth study, in line with their academic and future professional goals, often achieve high results, highlighting the importance of providing learners with flexibility in choosing materials and tasks, making the learning process more targeted and motivated.

Lagging students facing difficulties in learning require special attention and support from universities [5]. The development of individualised approaches to education and the provision of additional resources can help them improve academic performance and increase their level of engagement in studying disciplines.

The analysis of LMS data offers new opportunities for optimising educational processes [6, 7]. Analytics and advanced technologies, such as artificial intelligence and machine learning, can significantly enhance educational systems' ability to adapt to students' needs and preferences and offer personalised learning trajectories.

The study of student behaviour in the electronic educational environment has become a significant theme for academic papers as educational technologies continue to evolve and permeate all aspects of higher education. This review examines key research and scientific papers dedicated to analysing students' behavioural patterns using data from LMS and other electronic educational platforms. Based on the literature review, the authors identified three directions of scientific research.

Several studies focused on applying learning analytics and machine learning methods to analyse LMS data to identify patterns in student behaviour [8, 9]. These methods automatically detect patterns related to performance, engagement, and the risk of dropping out. Several published papers illustrate the use of data on student interactions with course materials, forums, and tests to predict performance and identify students needing additional support.

Research has also revealed various behavioural models and learning strategies among students using electronic educational resources [10-13]. Several articles describe various approaches to learning, including active participation in interactive tasks, passive listening to lectures, and strategic use of resources to maximise performance. These studies highlight the importance of individualising the educational process to match different learning styles and preferences.

A number of studies also emphasised the significant role of social interaction and collaboration in the electronic educational environment, reflecting the influence of social networks and collaboration tools on student learning, facilitating knowledge exchange and mutual support [14-17]. It indicates the potential of social media and other platforms to create a more engaged and interactive community.

The research presented in this article focuses on the first two groups of studies, which are the closest to the subject area studied by the author.

2.OBJECTIVES AND METHODS

The body of the broadside consists of add up to sections that present the main outcomes. These sectors should be organized to best existent the material.

This article describes a study to identify students' behavioural patterns using data from the Moodle Learning Management System (LMS) [18]. The study set out the following objectives:

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- Data Collection from the LMS. This task involved studying and describing the various types of data available in the LMS [19] and developing a methodology for data collection and preliminary processing for subsequent analysis.

- Data Analysis to Identify Behaviour Patterns [20]: Statistical analysis, machine learning, and clustering methods were applied to process the collected data to identify students' behaviour patterns in the electronic educational environment. Key characteristics and parameters that facilitate the classification and interpretation of behavioural models were identified.

- Classification of Identified Patterns. A classification system for the identified behaviour patterns was determined, including active participation, passive observation, learning strategies, and engagement in the course [21]. The correlation between different behavioural patterns and student performance was explored.

Types of LMS data used for the study:

- Activity Logs: Serve as the primary data source in the LMS, recording every user action within the system. It includes login and logout times, pages viewed, tasks completed, and forum activity.

- Grades and Feedback: Systematic collection of students' grades, test results, and received feedback provides data on their performance and understanding of the material.

- Interaction with Content: Data on how students interact with learning materials, such as the time spent on specific resources and which materials are viewed most frequently.

- Communications: Data on messages and discussions in forums, chats, and other communication tools within the LMS can provide insights into social interactions and collaborative learning among students.

Methods of data analysis to identify behaviour patterns:

- Statistical Analysis: Using statistical methods to analyse trends, compare groups, and identify correlations between variables.

- Machine Learning: Applying machine learning algorithms to classify students by behaviour types and identify learning problems.

- Clustering: Allows the identification of different groups of students demonstrating similar behaviour patterns in the LMS, grouping students by similar behaviour patterns without pre-defined categories.

3.CALCULATIONS

The conducted investigations evaluated overall trends, distributions, and relationships between variables in the data. Machine learning methods were used to process the data obtained from the LMS and identify complex patterns not always apparent in traditional analysis.

For the study, a group of 60 students enrolled in a programming course was selected. After applying the K-means clustering algorithm to the online course students based on collected data, the following distribution of students across clusters was obtained:

- Cluster 0: 14 students
- Cluster 1: 17
- Cluster 2: 12 students
- Cluster 3: 17 students

Statistical indicators such as average time in LMS, forum activity, task completion, and test results were calculated for each cluster. Below is a Python code snippet for calculating statistics:

```
# average values for each cluster
cluster_means = kmeans.cluster_centers_
# calculation of statistics for each cluster
        statistics = {
        "Cluster": [],
        "Mean Time in LMS (hours)": [],
        "Mean Forum Activity (posts)": [],
        "Mean Task Completion (%)": []
        "Mean Test Results (%)": []
}
for i, mean in enumerate(cluster_means):
        statistics["Cluster"].append(f"Cluster {i}")
        statistics["Mean Time in LMS (hours)"].append(round(mean[0], 2))
        statistics["Mean Forum Activity (posts)"].append(round(mean[1], 2))
        statistics["Mean Task Completion (%)"].append(round(mean[2], 2))
        statistics["Mean Test Results (%)"].append(round(mean[3], 2))
statistics
```

Table 1 delineates the outcomes derived from the computational analysis conducted, offering a comprehensive visual representation of the statistical indicators obtained.

Table 1. Statistical indicators of the clusters

Clust. no.	Av. time in LMS (hours)	Av. forum activity (messages)	Av. task completion (%)	Av. test scores (%)
0	3,15	15,15	78,07	25,78
1	4,64	29,25	76,9	70,75
2	5,42	20,48	16,14	82,48
3	4,94	23,69	28,04	27,61

Note that students in Cluster 2 showed high test scores with a relatively low percentage of task completion, which may indicate their ability to perform well in exam tasks despite low activity in coursework. At the same time, Cluster 1 demonstrated high forum activity and good academic results, underscoring the value of social interaction and active participation in discussions for successful learning.

Guided by the statistical indicators obtained from the calculations, an analysis of the relationship between students' behavioural characteristics and their level of academic achievement was conducted. Key indicators considered were the average values for task completion and the average values for final testing outcomes. The results are presented in Table 2.

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Table 2. Key Indicator values by cluster

Cluster No.	Average task completion, %	Average test scores, %
0	78,07	25,78
1	76,9	70,75
2	16,14	82,48
3	28,04	27,61

From the analysis, the authors concluded that the low test scores in Cluster 0, despite a high level of task completion, could indicate a poor understanding of the material or ineffective test preparation. Such academic performance can be assessed as an average or low level. The indicators of students in Cluster 1 reflect high performance, attributed to balanced activity in the course and good results in task completion and testing. In Cluster 2, students show high testing results with a low level of task completion. It can be characterised as solid examination skills and the ability for compelling independent study. Such results can be classified as a high level of achievement. The last cluster demonstrates a low level of performance across all indicators, clearly indicated by low values in both tasks and testing. This phenomenon results from apparent difficulties in learning among students in this segment.

4.RESULTS

Based on the analysis of statistical indicators and the correlation of each cluster with the level of performance, the types of each cluster in the context of the educational process have been identified.

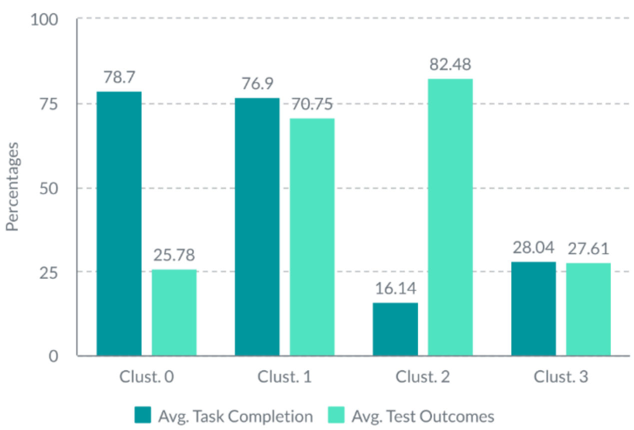

Fig. 1: Analysis of the relationship between clusters and performance level

Type 1 - "Hardworking but stressed during tests": This group of students is characterised by high task completion rates with low final test scores. This phenomenon may indicate increased tension, stress, or difficulties in taking exams despite active academic work.

Type 2 - "Balanced high performers": Students in this group perform well in both tasks and tests, indicating a high level of engagement in the learning process and effective material assimilation.

Type 3 - "Exam masters": Despite a low percentage of task completion, students of this type exhibit high test scores. This phenomenon may indicate the ability to absorb information and effectively apply knowledge quickly under exam conditions.

Type 4 - "In need of support": This group of students has low task completion and test results indicators. It suggests possible learning difficulties or a lack of motivation, making them most likely to need additional support and resources.

5.CONCLUSIONS

The data obtained from the study allow for conclusions about the relationship between students' behavioural patterns and their level of performance. Clusters 1 and 2 demonstrate high performance, but for different reasons: the former due to active participation and good preparation, the latter thanks to strong examination skills. Clusters 0 and 3 show average and low-performance levels, respectively, indicating the need for additional support and resources to improve their educational outcomes. These conclusions serve as a basis for developing targeted educational strategies to enhance performance levels, depending on students' cluster affiliation.

The results are not purely theoretical postulates but are oriented towards practical application. Specifically, based on the identified patterns, a series of strategies can be developed to improve the effectiveness of the educational process in each group, for example, "Hardworking but stressed during tests," providing additional support for stress and anxiety management during exams, organising training sessions on stress management techniques, conducting practical classes, and mock tests. The "Balanced high performers" can be supported and encouraged through independent research and in-depth study of the material; for "Exam masters," additional tasks and projects that stimulate interest in expanding knowledge in the studied subject area, additional activities to stimulate critical thinking, opportunities for demonstration and practical application of knowledge and skills in real situations. For the lagging group, it is possible to identify needs and develop personalised learning plans, provide additional learning materials, and organise group and individual classes to offer help and support in learning. Also, systematic monitoring of students' progress is recommended to identify problems early and respond to them promptly.

The study highlights the significance of integrating data analytics into the learning process to identify and support students' various learning needs. Understanding and applying such methods can help educational institutions create more engaging, effective, and adaptive learning environments, contributing to the success of a larger number of students.

6.DISCUSSIONS

Exploring student behaviour patterns using Learning Management Systems (LMS) data has not only opened new avenues for understanding but also holds transformative potential for enhancing the educational journey. This discussion

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aims to delve into the intricacies of the findings, examining the implications and potential strategies for educational advancement based on the identified patterns of student interaction and performance within the electronic learning environment.

Our analysis's core is the discernment of distinctive behavioural clusters, each presenting unique characteristics and learning modalities. The classification into "Hardworking but stressed during tests," "Balanced high performers," "Exam masters," and "In need of support" not only sheds light on the varied approaches students adopt towards learning but also underscores the multifaceted nature of academic achievement. The divergent pathways to learning success or difficulty suggest that educational interventions must be as heterogeneous as the student body they aim to support.

The study's revelation that active participation correlates strongly with academic achievement is particularly noteworthy. It reiterates the significance of engagement with the learning material and discussion participation, affirming the hypothesis that interactive and immersive educational experiences are paramount for deep learning. The findings advocate for implementing pedagogical strategies that foster active learning environments where students are encouraged to contribute, question, and collaborate, enhancing their comprehension and retention of knowledge.

Conversely, the distinction between those students excelling in exams despite lesser engagement with course tasks ("Exam masters") and those struggling despite high task engagement ("Hardworking but stressed during tests") offers an intriguing perspective on the nuances of learning efficacy and assessment strategies. Traditional metrics of academic success, such as test scores and task completion rates, may not fully encapsulate a student's understanding or potential. This insight prompts a reevaluation of assessment methods, advocating for a broader, more inclusive approach that recognises and accommodates diverse learning styles and competencies.

The identification of students 'In need of support underscores the critical role of personalised educational strategies. The provision of targeted support mechanisms, such as tailored learning materials, mentoring, and enhanced feedback channels, is not just beneficial but essential in addressing the unique challenges faced by these students. The adoption of an individualised learning approach not only aids in bridging educational gaps but also contributes to the cultivation of a supportive, inclusive academic environment that recognises and values diversity in learning processes.

Furthermore, the study underscores the importance of leveraging data analytics in educational settings. The ability to classify students into distinct behavioural clusters based on their interaction with LMS data is a testament to the potential of machine learning and artificial intelligence in crafting personalised learning experiences. By harnessing the power of data analytics, educational institutions can move towards a more adaptive and responsive educational model that dynamically adjusts to meet the evolving needs and preferences of the student population.

The research presents a compelling case for integrating data-driven insights into educational strategies. By understanding and responding to the diverse behavioural patterns of students, educators can devise more effective, personalised approaches to teaching and learning. The findings advocate a paradigm shift towards a more engaged, inclusive, and adaptive educational environment where every student has the resources and support necessary to realise their full academic potential. As we move forward, these insights must guide the development of educational policies and practices, ensuring they are aligned to foster academic excellence and equity for all students.

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