Uncovering Student Engagement and Performance in Applied AI in Finance: A Learning Analytics Approach

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Abstract: The product of the Erasmus+ project, Transversal Skills in Applied Artificial Intelligence (TSAAI), is the educational framework FuturIA, which offers a massive open online course focusing on the development of highly demanded transversal skills. The platform utilizes a unique pedagogical approach centered on solution-practice triplets and personalized learning pathways, aiming to adapt to individual student needs and foster effective skill acquisition. The TSAAI expert course was piloted by 30 students from universities participating in the project, enabling the consortium to refine the curriculum and teaching methodologies before the official launch of FuturIA. This study focuses on assessing the learning analytics of students, including descriptive analysis of log data, correlations between grades and course activities, clustering and a gender-based comparison of students' success and engagement.

1 INTRODUCTION

The increased utilization of AI technologies has led to a substantial increase in demand for professionals proficient in AI, which the current formal educational system is unable to meet, creating a gap between the profile of employees available on the labor market and the industry's escalating needs (Kujundziski et al., 2024). Hence, to navigate the evolving landscape of AI-driven job transformation, upskilling and/or reskilling initiatives are crucial to equip individuals with the requisite competencies (Wang et al., 2024). To work effectively alongside AI systems, individuals must be equipped with a range of technical, soft, and hybrid skills (Du, 2024), which emphasize the importance of adapting educational and training programs and promote a culture of continuous learning and professional development. Alongside knowledge specific to the profession, education systems must prioritize the cultivation of transversal skills, reflecting the need for the development of critical thinking, problem-solving, and digital skills among students (Rudolph et al., 2024), as well as adaptability, communication, and interpersonal skills (Kujundziski et al., 2024).

The digital evolution necessitates modifications to formal higher education curricula. Due to the rapid pace of technological advancements, the transformation of study programs faces challenges, emphasising the need for collaboration between businesses and educators to ensure that academic programs align with the demands of the labour market (Bobițan et al., 2024).

Aiming to diminish the discrepancy between basic AI knowledge and the growing demand for experts in AI applications across various fields, the consortium of the Erasmus+ project Transversal Skills in Applied Artificial Intelligence (TSAAI) developed an educational platform called FuturIA, integrated into the learning management system (LMS) Moodle. For this purpose, the online course was developed, consisting of nine modules that cover AI methods, tools, methodologies, and the application of AI in various areas, including science, finance, industry, Information and Communication Technologies (ICT), and humanities. The online TSAAI expert course includes written and audio-visual educational resources covering advancements in applied artificial intelligence, created to provide

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attendees with highly demanded transversal skills (Kujundziski et al., 2024).

FuturIA distinguishes itself through its unique pedagogical approach, which is rooted in the creation of solution-practice triplets including presenting a problem that resonates with students' experiences, offering an intuitive and logical methodology for addressing the problem, and providing a practical, step-by-step guide to implement the proposed solution, carefully designed to facilitate effective learning and skills' acquisition (Kujundziski et al., 2024). This hands-on approach to learning is complemented by a strong emphasis on transversal skills, equipping learners with the competencies necessary to succeed in multidisciplinary environments and adapt to the evolving demands of the AI-driven landscape (Kujundziski et al., 2024). Providing customized educational pathways that consider individual learning preferences, the FuturIA platform encourages personalized learning, adapting to students' learning paces and knowledge levels (Demartini et al., 2024), i.e., following students' learning analytics. By collecting, analyzing, and reporting data about learners and their learning environments, such as student interactions with online learning platforms, assessment results, and demographic information, one can identify learning patterns and trends to understand and improve learning experiences.

Before its official launch, the pilot TSAAI expert course was tested by 30 students with diverse educational backgrounds from higher education institutions participating in the TSAAI project over a four-month period, from September to December 2024. Piloting the online course, and thus, the FuturIA educational platform, is necessary for testing and adapting the system before its full launch for massive use. This involves making adjustments to the curriculum, training materials or teaching methods, which are important for the sustainability of this learning framework.

Learning analytics is a useful tool for assessing the taeching and learning process and course effectiveness (Wong et al., 2025). Log analysis give opportunities to get insights from the user engagement in online education settings (Ademi & Loshkovska, 2019b). Especially AI driven learning analytics is a potential for the personalized feedback in learning systems (Vashishth et al., 2024)

Thus, this study aims to assess the learning analytics of students who have experienced the TSAAI online course, including descriptive analysis of log data, such as quiz submissions, lessons viewed, and time spent on each activity. Additionally, it examines the correlations between grades and course activities, as well as a comparison of success based on gender. It also uses clustering to classify the students.

2 METHODOOLOGY

This study employed a combination of data mining, statistical analysis, and correlation analysis to explore patterns of learner engagement and performance in the pilot online course Applied AI in Finance. The methodological process included participant identification, data collection and preprocessing, data transformation, and the application of analytical techniques to quantify learner behaviors.

2.1 Participants

The participants of this study were students from six different countries, all of whom were enrolled in the pilot implementation of the Applied AI in Finance course. These students came from various higher education institutions involved in the TSAAI (Transforming Skills in Applied Artificial Intelligence) project. The cohort represented a diverse mix of educational and cultural backgrounds, providing a rich context for analyzing engagement and learning behaviors in an international, digitally mediated environment.

2.2 Data Collection and Processing

Data was collected from the FuturIA platform, which uses Moodle as its learning management system. The primary source of data was Moodle log files downloaded in .csv format. These log files captured granular details of learner interactions with the course, including events such as page views, quiz attempts, resource accesses, and system-generated updates. Each record contained the following fields:
Time, User full name, Affected user, Event context, Component, Event name, Description, Origin, and IP address.

To complement the behavioral data, course grade files were also exported from the platform. These included key performance indicators such as quiz results and overall course grades. The grade data was then merged with the log data based on user identifiers to support integrated analysis of engagement and performance.

Before processing the data is anonymized to keep the privacy of the learners. For this purpose, each learner is assigned a user ID.

2.3 Data Cleaning

To ensure the analysis focused strictly on student activity, data preprocessing steps were applied to filter out logs generated by instructors, system administrators, and automated background processes. Duplicate or irrelevant entries were removed and missing or malformed data were identified and handled appropriately. Special attention was paid to encoding and formatting issues to enable consistent processing across data sources.

2.4 Data Transformation and Integration

Log records were transformed into aggregated activity counts per user, capturing the frequency of key learning actions (e.g., viewing a course module, submitting a quiz). These behavioral indicators were standardized and combined with the grade data to form a unified dataset. This integration enabled a multi-dimensional analysis that connected learner behavior with academic outcomes.

2.5 Data Exploration and Analysis

To quantify learner interaction, we introduced a composite metric called the Engagement Score. This score was calculated by summing the counts of six key activity-based events for each user (Table 1).

Table 1: Event types extracted from the logs.

Event Name	Description
Course activity completion updated	Tracks marking of course items as complete
Course module viewed	Indicates views of individual learning modules
Course viewed	Counts course landing page accesses
Quiz attempt submitted	Shows actual attempts at submitting quizzes
Quiz attempt started	Captures initiation of quiz activities
Quiz attempt viewed	Shows how often users accessed quiz details

This metric served as a proxy for student engagement within the platform. Using this measure, participants were segmented into Low, Medium, and High engagement levels via quantile-based classification. Descriptive statistics, histograms, and correlation matrices were then used to explore the relationship between engagement and performance (e.g., quiz percentage and course total grades). These analyses helped identify patterns and discrepancies across different engagement tiers.

2.6 Clustering

Clustering analysis was conducted to identify distinct groups of students based on their activity patterns and academic performance in the Applied AI in Finance course. By grouping students with similar behaviors, such as quiz attempts, course views, and test scores, this unsupervised learning approach aimed to uncover hidden patterns in learner engagement.

3 RESULTS

3.1 Student Engagement

Engagement score provides a comprehensive measure of user participation by integrating various dimensions of engagement, including navigation activities (such as page views), active involvement (like starting or submitting assignments), and progress tracking. By offering a blended perspective, the score proves valuable for identifying differences between highly engaged and passive learners (Ademi & Loshkovska, 2020), understanding how engagement correlates with academic performance (e.g., final grades), and flagging students at risk due to consistently low interaction levels. Table 2 shows the summary of engagement levels of the students.

Table 2: Summary by engagement level.

Engagement Level	Avg. Engagement Score	Avg. Quiz %	Avg. Course Total
Low	9.73	95.31%	19.06
Medium	27.62	79.17%	90.28
High	147.60	96.88%	1234.21

High-engagement students consistently demonstrated significantly higher course totals and quiz scores, highlighting the strong link between sustained participation and academic success. In contrast, students categorized as having medium engagement showed moderate activity levels but underperformed on assessments, suggesting they may benefit from targeted academic support or intervention strategies. Interestingly, some low engagement users achieved unexpectedly high quiz scores, which may indicate prior subject knowledge or strategic, focused studying rather than ongoing participation. This pattern emphasizes the need to consider multiple dimensions of learning behavior when interpreting engagement data (Wiedbusch et al., 2023).

Figure 1 shows the distribution of engagement.

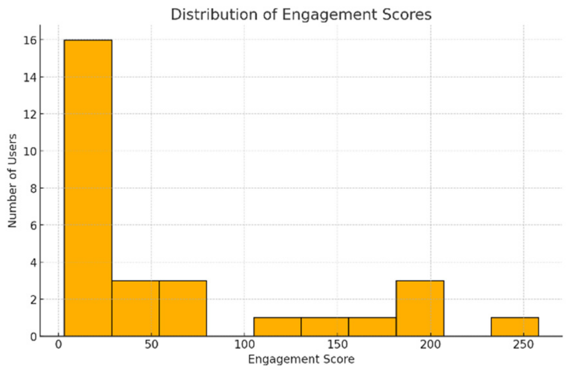

Figure 1: Distribution of Engagement Scores across users.

The distribution of engagement scores among users reveals a right-skewed pattern, indicating that while a few users are highly active, the majority show relatively low levels of engagement. Most users have engagement scores below 50, with the median at just 21, suggesting that half of the participants performed fewer than 21 key interactions (such as viewing modules or submitting quizzes). A small group of users, however, demonstrated exceptionally high engagement, with scores reaching up to 258, significantly raising the average. This disparity highlights a common pattern in digital learning environments, where a core group of highly engaged learners coexists with a larger group of minimally active participants (Caspari-Sadeghi, 2022). Such insights can be useful for identifying learners who may need additional support or encouragement to participate more actively. Table 3 showing the summary statistics of engagement score also displays positively skewed distribution.

Table 3: Summary statistics for the Engagement Score.

Statistic	Value
Count	30 users
Mean	62.21
Std. Dev.	74.47
Min	3.00
25th Percentile (Q1)	13.00
Median (Q2)	21.00
75th Percentile (Q3)	69.00
Max	258.00

3.2 Gender Based Engagement

To explore potential differences in learning behavior and performance, a gender-based analysis was conducted using student interaction logs and grade data from the Applied AI in Finance course. Gender was inferred from students' names to examine patterns in course engagement, quiz participation, and official test performance. While the primary goal was to identify whether engagement or outcomes varied meaningfully between male and female students, the analysis was approached with caution due to the limitations of name-based gender identification and the relatively small sample size. Figure 2 shows the average user activities by gender.

The statistical test compared activity levels between male and female users using independent t-tests. Among the various types of user engagement analyzed, only the "Course viewed" activity showed a statistically significant difference between genders ($p = 0.045$), indicating that male users tend to view the course more frequently than female users. For all other measured activities—course activity completion, module views, grade updates, and grade report views—there were no statistically significant differences observed ($p > 0.05$). This suggests that, aside from course access frequency, engagement patterns are generally similar across genders.

3.3 Course Success

The course contained 20 topics and a quiz for each topic. In the end of the course there was an official test.

The summary statistics of student quiz scores across Topics 1 to 20 reveal a pattern of consistently high achievement, with limited variability in most topics. Specifically, quizzes from Topics 2, 4, and 5 demonstrate perfect performance across all students, as indicated by their 100% mean scores and 0.00 standard deviation. This suggests that these quizzes were either too easy or well-aligned with student preparation.

In contrast, Topics 1 and 3 show slightly more variation. For Topic 1, the mean score is 94.67 with a standard deviation of 11.25, and scores ranging from 73.33 to 100. Topic 3 exhibits a similar pattern with a mean of 96.19, standard deviation of 10.08, and minimum score of 73.33. These topics may have presented more challenging material or revealed knowledge gaps among some students.

Although the summary includes placeholders for quizzes up to Topic 20, current data is only available for the first five. This limits broader trend analysis but already highlights a strong performance pattern among students, with most consistently scoring at or near full marks. The lack of variation in many topics could also impact the ability to draw meaningful

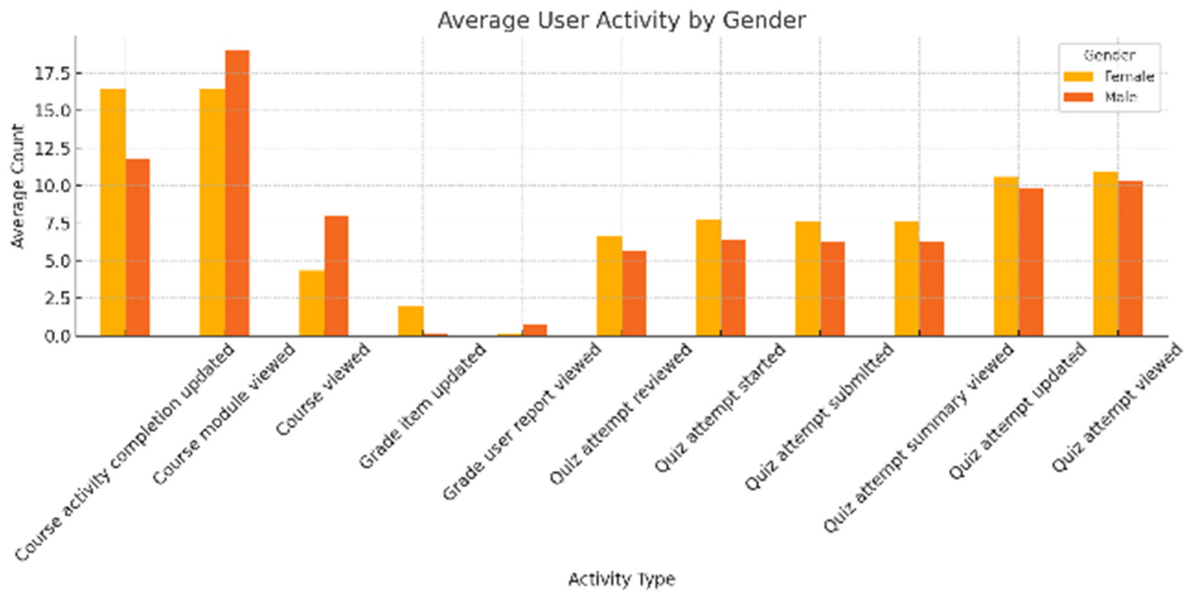

Figure 2 Average user activity by gender.

correlations with broader performance metrics like the official test grade.

Table 4 shows the summary statistics of the official test scores and the time taken to complete the test. Figure 3 is the scatterplot showing the relationship between Official Test Time (in seconds) and Official Test Grade (out of 20).

Table 4: Summary statistics for the official test score and time taken.

	Official Test Grade	Official Test Time (secs)
count	29	23
mean	15.26	655.91
std	8.02	421.8
min	0	154
Q1	16.25	350.5
median	20	494
Q3	20	870
max	20	1502

The scatterplot illustrates a wide range of test durations among students, with many achieving full marks (20/20) regardless of how much time they spent on the test. There is no clear linear relationship between time taken and performance—some students completed the test quickly and scored highly, while others took longer with mixed outcomes. Notably, a few students who spent a considerable amount of time on the test ended up with lower scores, which may suggest difficulties in understanding the material or external distractions during the assessment.

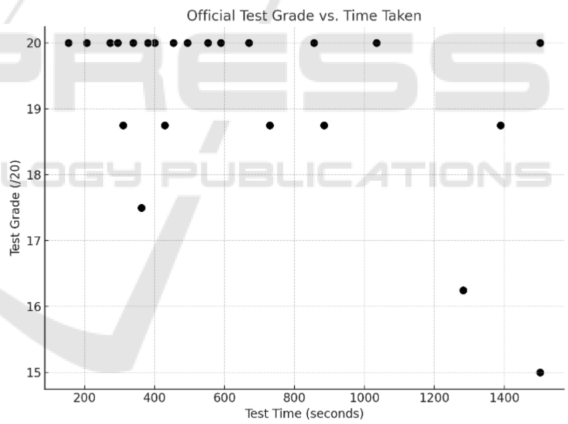

Figure 3 Official Test Grade vs. Official Test Time relationship.

3.4 Correlations

To better understand the relationships between student engagement and academic performance, a correlation analysis was conducted using key activity metrics and grade data from the course. The analysis focused on identifying how behaviors such as quiz participation, course views, and test durations relate to outcomes like quiz averages and official test scores. By examining these correlations, the aim was to uncover which types of engagement are most strongly associated with academic success, providing insights for enhancing future course design and learner support.

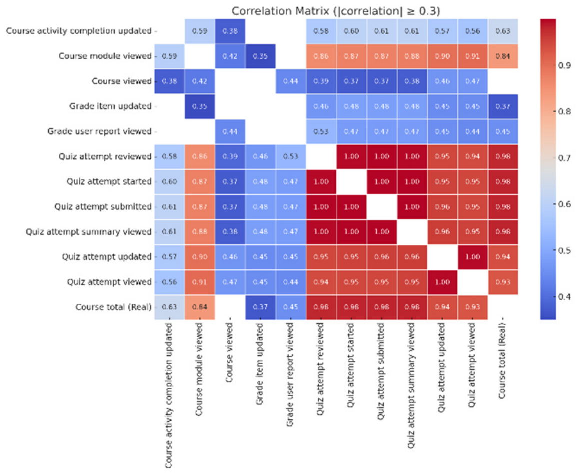

Figure 4: Correlation matrix activities vs grade.

The correlation matrix of significant features (where the correlation coefficient is ≥ 0.3 or ≤ -0.3) was visualized using a heatmap to reveal relationships between key course engagement metrics and student performance. A notable pattern emerged among quiz-related activities—such as quizzes submitted, reviewed, and viewed—which showed extremely high intercorrelation (above 0.9). This indicates that students who engage in one aspect of quiz activity tend to participate actively in others as well. Furthermore, these quiz metrics also demonstrated a strong positive correlation with the final course grade (Course total - Real), suggesting that consistent engagement with quizzes plays a central role in academic success. In addition to quiz activities, metrics such as "Course module viewed" and "Course activity completion updated" displayed moderate correlations with both quiz engagement and final grades, highlighting their contributory role in learning outcomes. Lastly, although less pronounced, features like "Grade item updated" and "Grade user report viewed" also exhibited modest yet meaningful correlations, reinforcing the importance of active monitoring and feedback in the learning process.

3.5 Clustering

The clustering analysis revealed three distinct groups of students based on their activity and performance patterns. Cluster 0 consists of students with moderate engagement: they viewed an average of 48.3 course modules and started 23 quizzes, while only lightly browsing the course itself (8.3 views). Despite this, they achieved perfect scores across all topics and the official test, suggesting they are efficient, high-performing learners who engage selectively. Cluster 1 includes students who browse the course content more frequently (22.0 views – the highest among clusters) and started 29 quizzes on average, yet achieved a slightly lower average official test grade of 18.75. This indicates a group of curious but slightly less consistent performers, possibly relying more on passive review. Cluster 2 represents the most actively engaged and highest-performing students, with the highest averages in course module views (84.5) and quiz attempts (31.0), while maintaining perfect scores across the board. This group demonstrates strong, consistent participation and academic success, reflecting deep engagement with the course material.

4 CONCLUSIONS

The analysis of student activity logs, quiz performances, and official test results from the Applied AI in Finance course reveals several key insights into learner engagement and achievement. Overall, students demonstrated high levels of success in quizzes, with average scores above 94% and many achieving perfect scores, particularly in Topics 2, 4, and 5. This consistency suggests strong content understanding or possibly low quiz difficulty in some topics.

However, the official test scores showed greater variability, with an average of 15.26 out of 20, indicating a broader range of mastery when assessed more comprehensively. The correlation between quiz scores and official test performance was weak, likely due to limited score variation in the quizzes. Activity metrics such as quiz attempts, course module views, and total engagement showed stronger alignment with test performance, especially among highly active students.

Clustering analysis further revealed distinct learner profiles — from highly engaged top performers to moderate users achieving similar grades. Gender-based analysis showed minimal differences in activity and performance, with only a slight statistical difference in course views.

In conclusion, while quiz performance was uniformly strong, meaningful differentiation among learners emerged only when considering broader engagement metrics and the official assessment. These findings underscore the importance of combining activity-based data with performance outcomes to obtain a clearer picture of student learning behavior and success.

As the course was a pilot study, number of students and the amount of data is limited. The small sample size and inconsistent quiz participation reduced the statistical power of the findings and limited their generalizability to broader student populations.

This analysis can be performed in a systematic way in the future trials of the FuturIA platform when there will be higher number of students. In the future analysis can be done dynamically before the end of the course so that they would give an early picture of the situation with the course and the students to take preventive actions for the dropouts and low scores (Ademi & Loshkovska, 2019a). These analyses could be embedded in the form of dashboards so that the instructors can see what is going on with the students and this may help them to take decisions about the ongoing teaching process. Learning Analytics dashboards are also helpful for the learners as they can see how they are performing within the group (Paulsen & Lindsay, 2024). Furthermore, these analytics can be used to provide adaptation and personalize the learning (Ademi & Loshkovska, 2025).

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