Optimizing Digital Learning Through Data Analytics and Natural Language Processing

Authors Redacted for Blind Review[1]

[1]Institution Redacted for Blind Review

Abstract

This study offers a detailed examination of student engagement and sentiment within CourseKata, a digital learning platform for statistics education using the textbook "Advanced Statistics with R (ABCD)" for College students. Leveraging extensive student interaction and feedback data, including pulse checks (periodic informal assessments gauging student sentiment and understanding of the course material) our analysis aims to identify and address the limitations of current engagement strategies. Discrepancies between positive pulse check responses and actual end-of-chapter performance were observed. Sentiment analysis, enhanced by t-SNE and clustered through Natural Language Processing (NLP) using a locally hosted Large Language Model (LLM), helped identify prevalent concerns such as time management and comprehension of complex concepts. By refining pulse checks, diversifying question types, and standardizing content length, we propose a model that significantly enhances learning outcomes and student engagement, offering a framework for adaptive learning environments

Keywords: Data Analysis, Natural Language Processing, Sentiment Analysis, t-SNE, LLM

1. Introduction

The rapid adoption of digital learning platforms necessitates effective mechanisms to evaluate and enhance student engagement and learning outcomes. CourseKata, an online statistics learning tool, represents a prime example of such platforms where understanding and improving student interaction is crucial. Despite the positive feedback typically reported via standard pulse checks, our preliminary analysis indicates that these measures may not accurately capture student performance dynamics, particularly as course content progresses and becomes more challenging. This study, therefore, explores the alignment between student-reported satisfaction and their actual performance, employing advanced analytical techniques to uncover deeper insights and propose actionable solutions.

2. Methods

Data Collection and Preprocessing

Our study utilized comprehensive data sets provided by CourseKata, which included detailed logs of student interactions, pulse check responses, and end-of-chapter performance scores. Initial data preprocessing was conducted using Python's Pandas library to clean and structure the data for analysis. This included handling missing values, filtering out outliers, and normalizing response scales to ensure consistency across different data sets.

Quantitative Engagement Metrics

To obtain a comprehensive view of student engagement through pulse checks, we aggregated data by response value and construct. Figure 1 classifies these responses, where higher ratings (4, 5, and 6 on a scale of 1 to 6) for constructs like Expectancy, General Utility Value, and Intrinsic Value indicate positive sentiments—reflecting confidence, usefulness, and interest, respectively. In contrast, the "Course Cost" construct, assessed by responses to statements like "I was unable to put in the time needed to do well in the previous chapter," uses lower scores (1 to 3) to denote a positive outcome, suggesting students managed their time effectively without feeling overwhelmed. Thus, lower ratings in the Cost construct also signal positive student experiences, aligning with the favorable perceptions observed in other constructs. This approach reveals that over 70% of responses across all constructs, including Cost, were positive, highlighting a generally favorable perception of the learning experience. This distribution underscores the need for accurate interpretation of each construct when analyzing pulse check data, as it reflects varied dimensions of student sentiment.

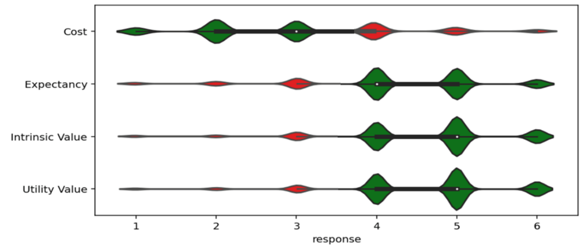

Figure 1: Frequency of Pulse Check Responses for Each Question Type.

Correlation Analysis

We analyzed the relationship between student engagement and performance using Spearman's rank correlation, chosen over Pearson's correlation for its ability to measure non-linear relationships. The analysis identified modest correlations, particularly within the Expectancy construct as shown in Table 1, highlighting the inadequacy of simple Likert-scale responses for capturing the full complexity of student learning experiences. In response, we propose refining the pulse check system by focusing on the most predictive constructs and expanding the response scale to a 1-10 slider for more nuanced feedback. Figure 2 underscores this by illustrating the misalignment between pulse responses and EOC scores across chapters, supporting our strategy to enhance response mechanisms to more accurately reflect actual performance and adapt more responsively to student needs.

Construct	Spearman Correlation
Cost	-0.138
Expectancy	0.197
Intrinsic Value	0.111
Utility Value	0.170

Table 1: Correlation between Response and EOC for each question type.

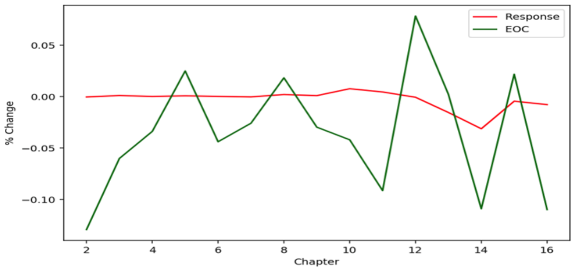

Figure 2: Percent Change in EOC and Expectancy Responses Between Chapters

Qualitative Sentiment Analysis

Sentiment analysis was performed on qualitative feedback collected at the end of each chapter. Using the t-SNE algorithm, a form of dimensionality reduction, we visualized the feedback data, facilitating the identification of patterns. The feedback was then clustered into distinct groups based on semantic similarity using a locally hosted Large Language Model (LLM). This method allowed us to interpret complex patterns in the data, identifying common themes and sentiments among students. After identifying clusters, we used the same LLM to generate concise summaries for each cluster, encapsulating the predominant sentiments and topics within the feedback. This automated approach enabled us to efficiently process large volumes of text and extract actionable insights without manual labeling. The summaries provided a high-level overview of student experiences and perceptions, which were crucial for developing targeted interventions to enhance the learning experience. Figure 3 provides a visual map of clustered student sentiments, categorized by common themes extracted through the LLM, though for a more detailed visual representation of these clusters and further insights into individual responses, please refer to Figures 9, 10 and 11 in the Appendix.

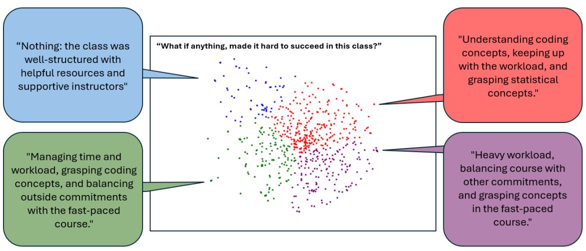

Figure 3: Summary of overall cluster sentiment with LLM usage.

Analysis of Pulse Check Responses

Our investigation into the pulse check responses uncovered a consistently high rate of positive feedback across all chapters, as illustrated in Figure 4. This trend persisted despite varying chapter content and difficulty levels, which initially suggested a robust positive reception of the course material. However, this surface-level analysis contradicted the deeper performance metrics derived from end-of-chapter assessments. Figure 5 exposes a decline in average end-of-chapter scores as students progressed through more challenging material, indicating a discrepancy between perceived understanding and actual performance. This finding suggests that while students may feel confident during learning, this confidence might not fully translate into mastery of the material.

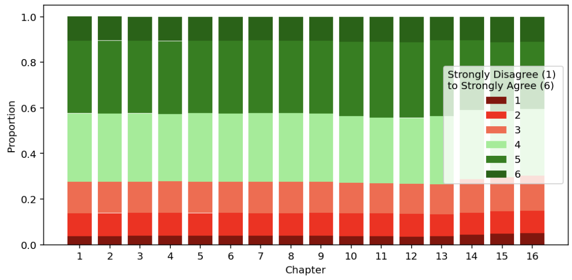

Figure 4: Proportion of Pulse Check Responses for Each Chapter

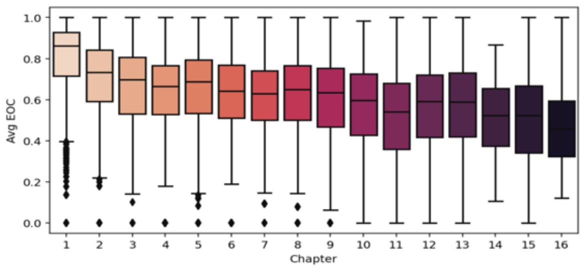

Figure 5: Distribution of EOC Values for Each Chapter

3. Results

Implementation of Recommendations

Based on the insights gained from our analyses, we propose several changes to improve the CourseKata platform. These include modifying the pulse check system to reduce response fatigue, diversifying question types to enhance engagement, and standardizing content length to mitigate content overload. Figure 6, for example, depicts how as students progressed through chapters, their average EOC scores tends to decrease regardless of how much time was spent on the chapter. Each recommendation is therefore backed by data-driven evidence from our analyses, ensuring that the proposed changes are tailored to address specific issues identified through our study.

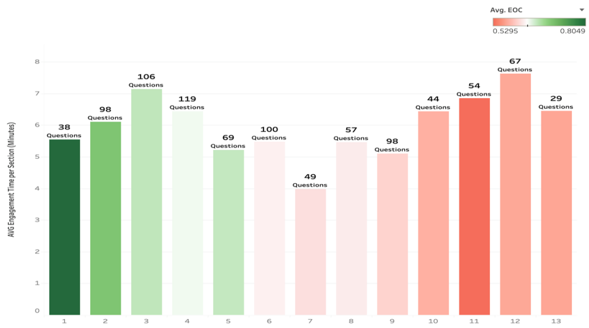

Figure 6: Average Engagement Time and Performance Per Chapter

Sentiment Analysis and Its Impact on Course Adjustments

Sentiment analysis, illustrated in Figure 3, clusters student feedback to reflect various impacts of the course on learners. Key concerns identified include time management and the balance between coursework and external commitments. This analysis helped pinpoint improvement areas, such as the notable finding from Figure 7 that videos receive over 90% watch time, suggesting a deeper engagement with video content. Based on this, we recommend adding more videos and interactive elements to further engage students and enhance the learning experience. Figure 8 shows that around 70% of assessment methods are multiple-choice questions, indicating a lack of variety. We propose diversifying assessment types by introducing interactive formats like connecting concepts or drag-and-drop questions. These changes aim to make learning more engaging and enjoyable, reduce workload pressures, and enrich educational content.

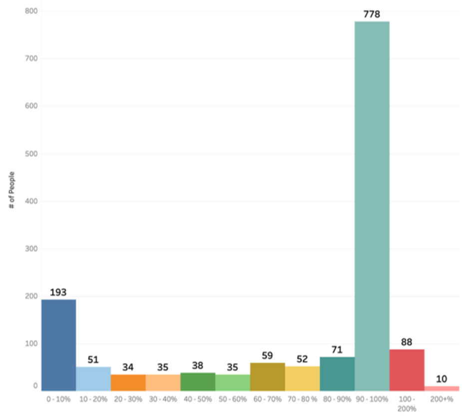

Figure 7: Distribution on Percent of Video Watch Time

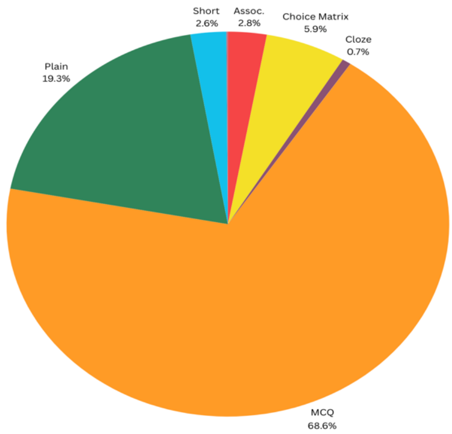

Figure 8: Question Type Frequency

4. Conclusion

The findings underscore the necessity for educational platforms to adopt more sophisticated analytics that align more closely with student experiences and performance outcomes. By simplifying and focusing pulse checks and integrating more dynamic and engaging content strategies, platforms like CourseKata can significantly enhance the educational experience of their users. These recommendations have been designed to be adaptable, allowing for implementation across various digital learning environments in order to foster more responsive and engaging educational practices.

References

Our dataset comprises student interaction logs, pulse check responses, and performance data from the online course "College / Advanced Statistics with R (ABCD)" offered by CourseKata. The data was provided as part of the 2024 ASA DataFest, which allowed us to explore real-world educational data in a competitive setting. This opportunity has offered unique insights into the dynamics of student engagement in digital learning environments.

Appendix

Detailed Analysis of Student Sentiment Clusters

This section of the appendix provides a deeper visual analysis of the student sentiments collected through the CourseKata platform. The figures presented below use dimensionality reduction and clustering techniques to illustrate the commonalities and differences in student responses, offering a granular view of how students perceive various aspects of the course. Figure 9 depicts how the team created an interactive environment where the user can hover over points to see individual responses and understand why they may have been clustered in that particular way. Figure 10 depicts the overall theme in each cluster, as analyzed and inspected by our team in a manual fashion. Finally, Figure 11 employs the usage of a locally hosted Large Language Model to quickly assess the overall theme of each particular cluster while giving a brief summary to aid in the understanding. Note that we conducted this sentiment analysis on three distinct questions (1) "When I think about this class, I'm concerned that..." (2) "Suggestions for future students taking the course" and (3) "What if anything, made it hard to succeed in this class?"

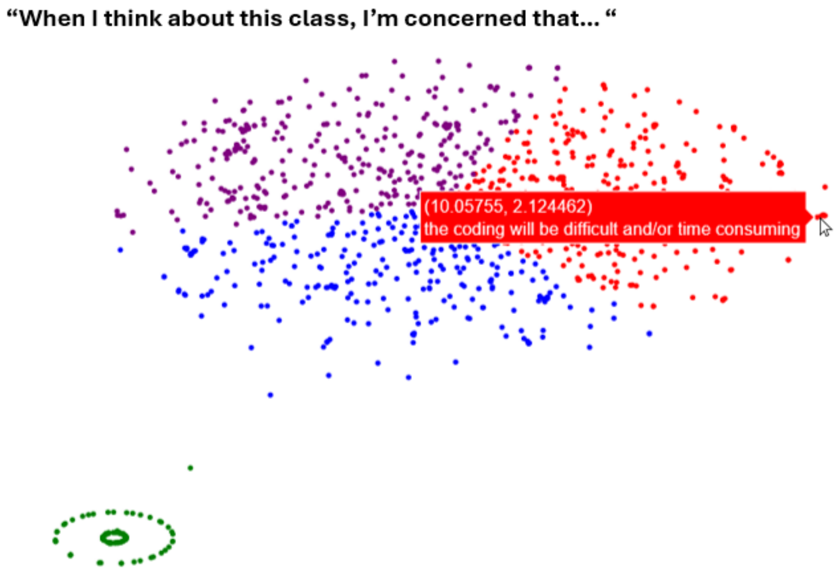

Figure 9: Answers to survey questions clustered based on their semantic similarity.

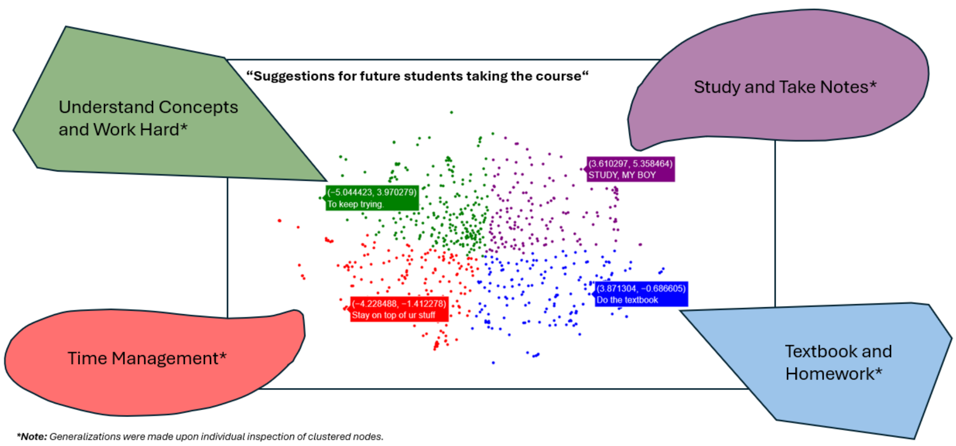

Figure 10: Clustering model depicting commonalities in student responses

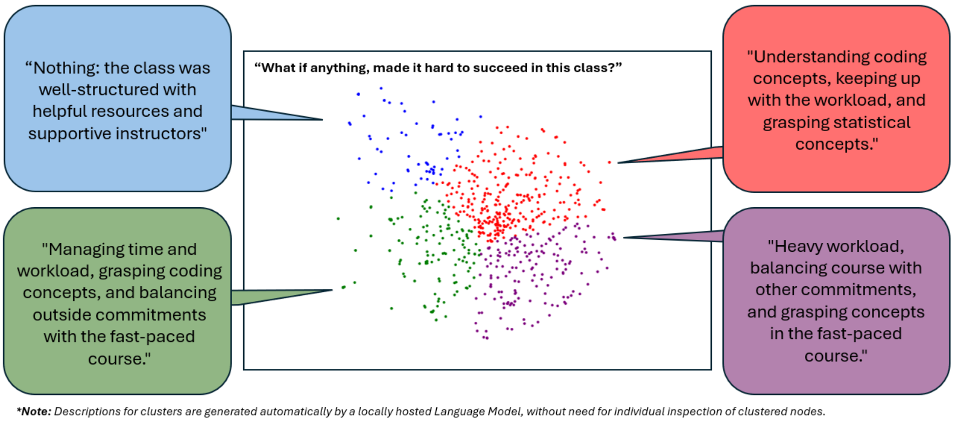

Figure 11: Summary of overall cluster sentiment with language model usage.