Engineering Educators Bringing the World Together
2025 ASEE Annual Conference & Exposition
Palais des congrès de Montréal, Montréal, QC • June 22–25, 2025
Paper ID #46698

Enhancing Object-Oriented Programming Education through Virtual Learning and Adaptive AI Technologies

Dr. Juan Felipe Calderón, Universidad Andres Bello, Viña del Mar, Chile

Juan Felipe Calderón received the bachelor's in computer science and MSc and PhD degrees in engineering sciences from the Pontificia Universidad Católica de Chile. He is an assistant professor in the Faculty of Engineering at the Universidad Andres Bello. His research interests are learning design supported by technology, innovation in engineering education, sustainability in cloud computing, technological infrastructure.

Matias Isaac Vargas

Enhancing Object-Oriented Programming Education through Virtual Learning and Adaptive AI Technologies.

Abstract

Virtual learning in programming has gained traction as an effective method for delivering advanced education, particularly in object-oriented programming (OOP). However, challenges remain in teaching complex topics like OOP. There are opportunities to advance by utilizing online platforms that offer more specialized yet flexible and adaptive learning paths. These platforms provide comprehensive resources, interactive coding environments, and collaboration tools, enhancing the learning experience. Their flexibility allows learners to progress at their own pace while accommodating varied schedules. Moreover, virtual learning enables real-time feedback and peer interactions, essential for mastering intricate OOP concepts.

With the primary objective of designing a flexible OO programming course for engineering students that incorporates multiple learning paths based on profile characterization, this paper aims to address the following question: What are the student profiles in an OOP programming course for an online engineering career? To this end, unsupervised learning techniques, such as clustering, were employed to categorize students based on patterns of LMS use behavior and academic performance associated with an existing instructional design for an online OO Programming course. We aim to uncover patterns that predict learning outcomes by analyzing behavioral data from virtual learning platforms. This approach seeks to optimize the adaptation of educational content to individual learning styles and needs, improving engagement and success in mastering OOP concepts. The findings of this research contribute to the broader application of AI in education, demonstrating the transformative potential of adaptive learning technologies in shaping the future of programming education.

Keywords: Virtual Learning, Object-Oriented Programming (OOP), Adaptive Learning, Artificial Intelligence (AI), Student Engagement

Introduction

The integration of virtual learning in programming education, particularly in object-oriented programming (OOP), has emerged as a significant trend driven by the need for flexible and adaptive educational methodologies. This shift is particularly relevant for engineering students, who often face complex programming concepts that require tailored instructional approaches. Online platforms offering specialized learning paths can enhance the educational experience by providing comprehensive resources, interactive coding environments, and collaboration tools. These features facilitate a deeper understanding of OOP and allow students to progress at their own pace, accommodating diverse schedules and learning modalities.

Research indicates that the design of online courses must consider the behavioral interactions of learners to optimize their learning outcomes. For instance, Park's study highlights the importance of structuring authentic learning tasks that encourage peer interactions, which can significantly influence student engagement and performance. However, it is important to note that this study did not find a direct relationship between behavioral interactions and performance scores. It suggests that peer interactions are beneficial but may not always correlate with improved academic outcomes[1]. This aligns with findings from Zen et al., who emphasize that project-based learning methodologies can enhance student engagement and academic achievement in online settings[2]. Such insights are crucial for developing an effective OOP course that meets the varied needs of engineering students.

Moreover, the flexibility of virtual learning environments allows for real-time feedback and peer interactions, essential for mastering intricate OOP concepts. The ability to receive immediate responses to coding exercises or project submissions can significantly enhance a student's understanding and retention of complex programming principles. This is supported by Eom's research, which suggests that early engagement in online courses, characterized by timely interactions with course materials and peers, positively correlates with academic performance [3]. Learning analytics tools can further facilitate this process by providing educators with insights into student behaviors and engagement levels, allowing for timely interventions when necessary [4].

In designing a flexible OOP course for engineering students, it is imperative to consider the diverse profiles of learners. Unsupervised learning techniques, such as clustering, can categorize students based on their learning management system (LMS) usage patterns and academic performance. This approach not only helps in identifying distinct student profiles but also aids in predicting learning outcomes based on behavioral data. For example, Ciubotariu and Crivei's work illustrates the application of unsupervised data mining techniques to analyze student performance, highlighting the potential of such methodologies in educational contexts [5]. By uncovering patterns in LMS usage, educators can tailor course content and instructional strategies to better align with individual learning preferences and needs.

The transformative potential of adaptive learning technologies in shaping the future of programming education cannot be overstated. As highlighted by Gopal et al., the impact of online classes on student satisfaction and performance during the COVID-19 pandemic underscores the necessity for effective online learning strategies [6]. The ability to adapt educational content to suit various learning styles enhances student engagement and success, particularly in complex subjects like OOP. Furthermore, integrating artificial intelligence in educational settings presents opportunities for continuous improvement in course design and delivery, ensuring the educational experience remains relevant and effective.

The evolution of virtual learning in programming, particularly object-oriented programming (OOP), has underscored the importance of adaptability in educational frameworks. As the demand for personalized learning experiences grows, the need to incorporate adaptive technologies into online education becomes increasingly evident. Adaptive learning environments can significantly enhance the educational experience by tailoring content and instructional strategies to meet student's diverse needs. This adaptability is crucial in complex subjects like OOP, where learners may possess varying prior knowledge and learning preferences.

Research has shown that adaptability in virtual learning environments can improve student engagement and academic performance. For instance, Ewais and Troyer emphasize the importance of usability in adaptive learning environments, suggesting that the design and functionality of these systems can significantly impact student satisfaction and learning effectiveness [7]. Similarly, Wang et al. highlight the role of emotional competence and online learning readiness in academic performance, indicating that personal factors can significantly influence how students interact with adaptive learning technologies [8]Understanding these variables is essential for developing a flexible OOP course that can accommodate the unique needs of engineering students.

Moreover, integrating artificial intelligence (AI) in adaptive learning systems presents opportunities for continuous improvement in educational practices. Alshammari proposes a framework for designing adaptive virtual learning environments that consider various student characteristics, thereby enhancing the personalization of the learning experience [9]. This framework aligns with the findings of Guevara et al., who present a model for adaptive learning objects that emphasizes the importance of tailoring educational content to the competencies required in specific contexts [10]. Such models can be instrumental in creating a more responsive and effective OOP curriculum.

The application of virtual reality (VR) technologies in education further exemplifies the potential for adaptability in learning environments. Vaughan et al. provide an overview of self-adaptive technologies within VR training, noting that these systems can dynamically adjust to the learner's needs, enhancing the overall training experience [11]. This adaptability is particularly relevant in programming education, where immersive environments can facilitate more profound engagement with complex concepts. Additionally, the work of Lin et al. illustrates how VR can be utilized to create adaptive learning experiences based on individual learning styles, reinforcing the notion that personalized approaches can lead to better educational outcomes [12].

Furthermore, the COVID-19 pandemic has accelerated the adoption of virtual learning technologies, revealing challenges and opportunities for educational adaptability. Nayak's research highlights the impact of virtual learning on students' mental health, emphasizing the need for adaptive strategies that consider learners' emotional and psychological well-being [13]. This perspective is crucial for designing an OOP course that not only focuses on technical skills but also prioritizes the holistic development of students. Then, the following research question arises: What are the student profiles in an OO programming course for an online engineering career? This paper is structured in a methodological section, and the results are presented. Finally, the discussion and conclusion section presents the scope and projection of this research.

Methodological framework

This research aims to identify student profiles in an online object-oriented programming (OOP) course tailored for engineering students. A comprehensive methodological framework will be employed to achieve this, integrating quantitative and qualitative approaches to gather and analyze data effectively. The framework comprises several key components: participant selection, data collection methods, data analysis techniques, and identifying relevant variables influencing student profiles.

Participant Selection

The data regarding student interaction with the institutional LMS, Instructure Canvas, was provided by the Department of Analysis and Assessment of a prominent private university in Chile. The analyzed students are enrolled in fully online engineering programs. These programs are primarily designed for working adults seeking an academic degree in engineering, and they include eLearning activities supported by weekly sessions with a lecturer to reinforce learning. One important consideration regarding the focus group is the diversity in their backgrounds and knowledge of computer science—some students are completely new to the field, while others have prior experience. The sample includes 180 students enrolled in a first-year "Object-Oriented Programming" course, which is required for all fully online engineering programs. The course follows a traditional 12-week structure with a fixed learning path shared by all students. The data corresponds to the first, second, and third quarters of the 2024 academic year.

Data Collection Methods

Data will be collected through learning management system (LMS) analytics. LMS analytics will provide quantitative data on students' engagement levels, time spent on tasks, and completion rates. This data is critical for identifying patterns in student behavior, as highlighted by Yang et al., who discuss the significance of understanding persistence factors in online programs [13].

Data Analysis Techniques

The analysis will employ quantitative methods. For quantitative data, statistical techniques such as cluster analysis and regression analysis will be utilized to identify distinct student profiles based on their engagement patterns and academic performance. Cluster analysis will help categorize students into groups with similar characteristics, facilitating the identification of common traits among high-performing and low-performing students, as discussed by Wladis et al. in their exploration of student success in online STEM courses [14].

Identification of Relevant Variables

Several key variables will be examined in this study to understand their impact on student profiles in the OOP course and what is available by the institutional LMS. These variables include:

- FG: Final Grade (on the Chilean scale of 1.0 to 7.0).
- TA: Total Access to Online Content
- TSA: Total Synchronous Activities
- TFA: Total Formative Assessments
- AP: Average Posts in online forums

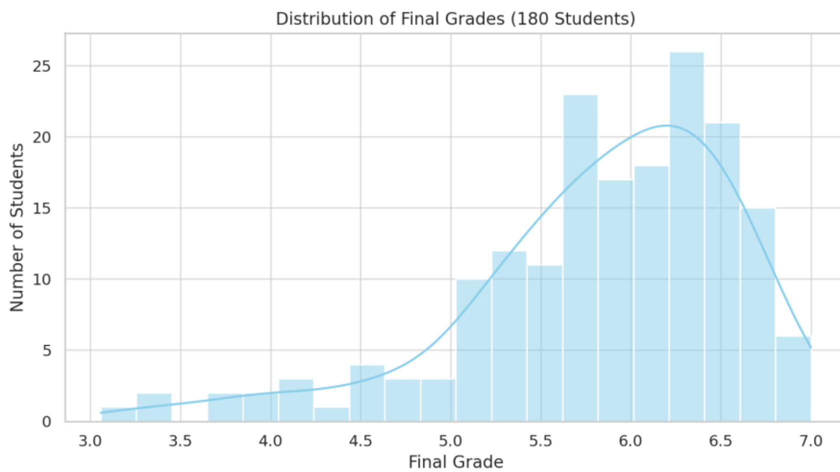

Fig. 1: Graph of the distribution of final grades for the 180 students.

Figure 1 illustrates the distribution of final grades for the 180 students enrolled in the online Object-Oriented Programming (OOP) course analyzed in this study. The final grade is composed of a weighted average of the presentation grade (70%) and the final exam score (30%), reflecting both continuous and summative assessment components.

The histogram reveals that a majority of students achieved grades within the 5.0 to 6.5 range, indicating a generally satisfactory performance across the cohort. However, a noticeable left-skew in the distribution highlights the presence of a non-negligible group of students whose final grades fall below the passing threshold. These students may be at risk and could benefit from targeted academic interventions

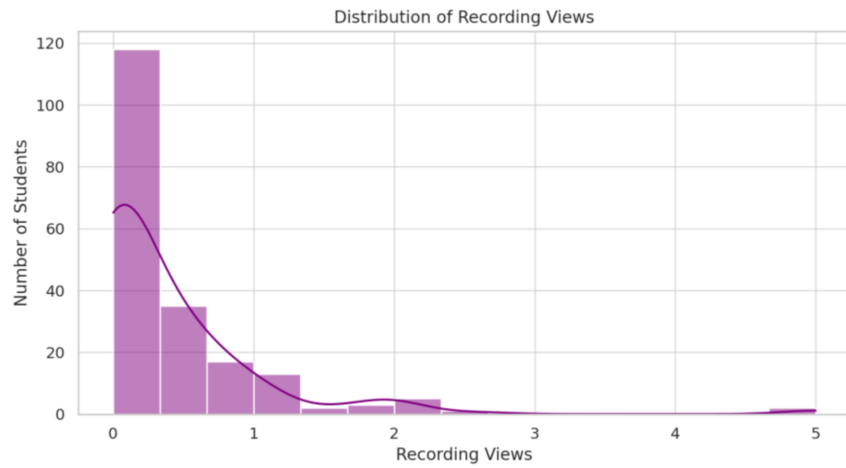

Fig. 2: Distribution of Recording Views

The histogram of recording views (Figure 2) shows that most students accessed recorded sessions between 0.5 and 1.0 times on average. A smaller subset engaged more frequently with recordings, suggesting the use of review strategies, potentially to compensate for missed live sessions or to reinforce understanding.

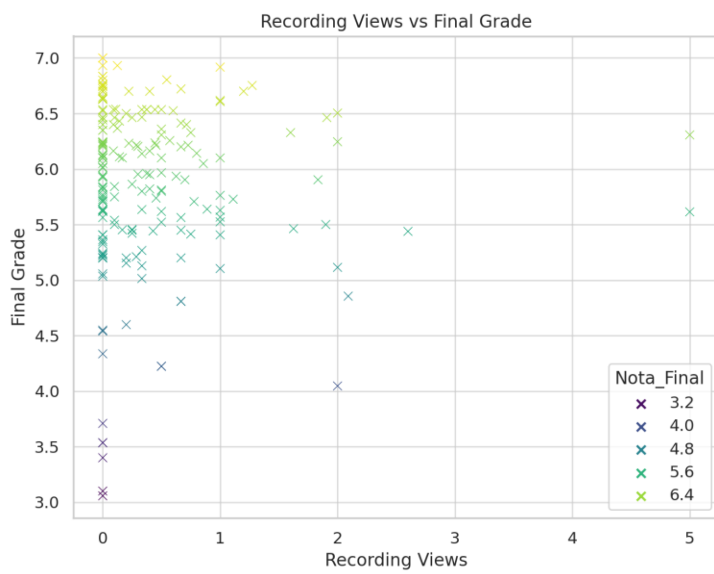

Fig. 3: Recording Views Vs Final Grade

The scatterplot in Figure 3 explores the relationship between the number of recording views and the final grade. A mild positive trend is observed, where students who engaged more with recorded content tend to achieve slightly higher final grades. However, considerable variability persists—some high-performing students accessed few or no recordings, indicating that success may be achieved through diverse learning strategies.

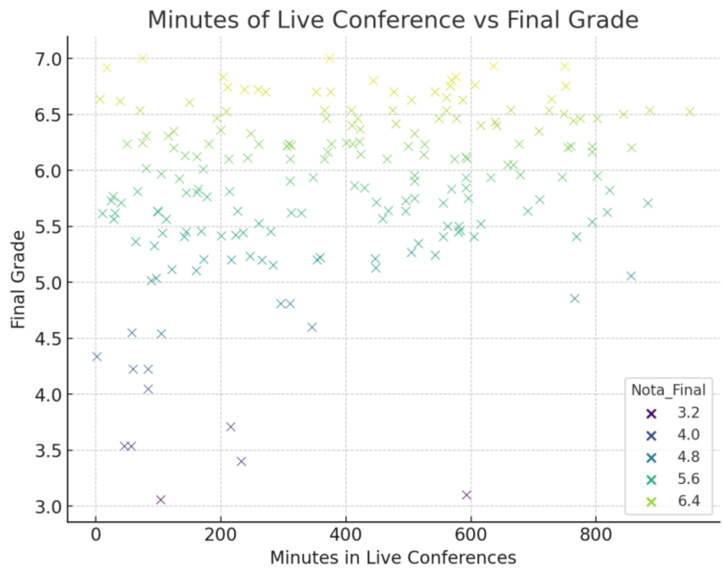

Fig. 4: Minutes of Live Conference vs Final Grade

Figure 4 shows the relationship between the total number of minutes spent in live video conferences and the final grade. A weak to moderate positive correlation is observed, suggesting that attending synchronous sessions contributes to better academic outcomes. However, the dispersion in the data implies that other factors such as asynchronous engagement, prior knowledge, or individual learning strategies also play a significant role in shaping final performance.

These exploratory insights suggest that both synchronous and asynchronous participation influence academic outcomes, but to varying degrees across student profiles. This justifies the application of unsupervised learning techniques to uncover latent patterns in engagement behaviors. The next section will present the clustering analysis, which aims to group students based on these interaction metrics and performance variables to better inform personalized educational interventions.

Results

A variety of techniques were utilized to conduct the cluster analysis effectively. Principal Component Analysis (PCA) was initially employed to eliminate irrelevant attributes by selecting pertinent and uncorrelated features. The presence of correlated variable pairs can lead to inaccuracies in the K-means algorithm's data grouping. Table 1 presents the correlation matrix among the variables, illustrating the degree of correlation between each pair. PCA was implemented to mitigate this issue. The PCA method from the Python Sklearn library was utilized, which requires specifying the desired number of principal components. We conducted

PCA for two and three principal components, resulting in two new data frames. To determine which data frame to use, we employed the Silhouette Coefficient, which assesses clustering quality in cluster analysis. This coefficient is calculated after applying the K-means algorithm to the data.

Table 1: Correlation Matrix

	FG	**TA**	**TSA**	**TFA**	**PA**
FG	1.00	0.55	0.37	0.25	0.02
TA	0.55	1.00	0.55	0.44	0.14
TSA	0.37	0.55	1.00	0.26	0.09
TFA	0.25	0.44	0.26	1.00	0.11
PA	0.02	0.14	0.09	0.11	1.00

Table 1 presents the correlation matrix for five key variables related to student performance in online Object-Oriented Programming (OOP) courses.

A **moderate positive correlation (r = 0.55)** is observed between **TA** and **FG**, suggesting that increased access to online content is associated with higher final grades. A similar correlation is found between **TA** and **TSA** ($r = 0.55$), indicating that students who frequently access course materials also tend to participate more in synchronous activities.

In contrast, **PA** shows a very weak or near-zero correlation with the other variables, including **FG** ($r = 0.02$), suggesting that participation in discussion forums may not have a direct impact on academic performance in this context.

These correlations help identify behavioral patterns in virtual learning environments, providing valuable insights to inform the design of adaptive educational interventions aimed at promoting engagement behaviors linked to academic success.

Next, the K-means algorithm was utilized to identify the optimal number of clusters. The optimal cluster count was determined using the "Jambu Elbow" technique, which involves plotting the sum of squared errors within each cluster for various values of k. This method seeks the "elbow" point on the graph, where the rate of decrease in the curve begins to level off. It was observed that the elbow could correspond to several cluster counts, specifically 3, 4, and 5. Initially, we considered three clusters and applied the K-means algorithm to the two new data frames containing two and three principal components. We subsequently calculated the Silhouette Coefficient to evaluate the clusters generated in both data frames.

Finally, the K-means algorithm was executed with the optimal number of clusters (k=3). We applied K-means to the two new data frames with two and three principal components and obtained the Silhouette coefficients of 0.39 and 0.31, respectively. The Silhouette coefficient ranges from -1 to 1, where a value close to one indicates well-defined clusters, while a low or negative value suggests potential misgrouping. Consequently, only the data frame with two principal components was selected for further analysis. The final clusters are presented in Figure 1.

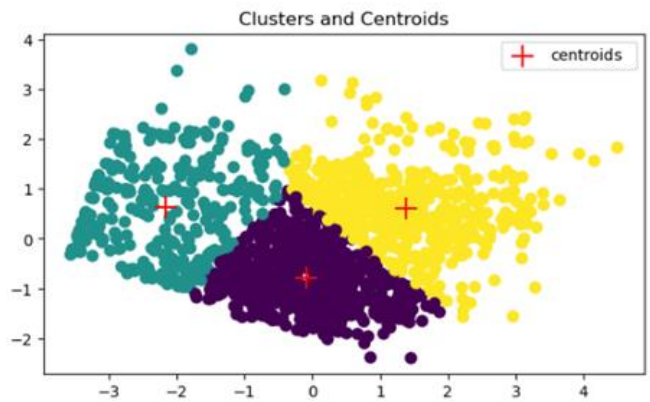

Fig. 2: Graph of the new data with the main components, and the red crosses represent the centroids of each group.

Statistical Description of Each Cluster

The analysis reveals that cluster 1 has a relatively high average final grade of 5.54. Students within this cluster exhibit the highest total access to online content (TA) and actively participate in synchronous activities and formative assessments, demonstrating moderate posting activity. This observation indicates a strong correlation between student engagement and academic performance. A similar trend is noted in cluster 3, which also displays a relatively high final grade of 5.26, albeit slightly lower than that of cluster 1. Students in this cluster engage less than those in cluster 1 but achieve commendable final grades. Their participation in formative assessments and forum discussions is notably lower. In contrast, cluster 2 presents the lowest average final grade of 2.05. This group exhibits the least engagement across all activities and records the lowest final grades. The more significant variability in grades within this cluster suggests a wide range of outcomes, potentially indicating the presence of outliers or a subgroup that performs well despite low levels of engagement.

Discussion

The clustering methodology employed in this research is consistent with previous studies on adaptive learning systems, which underscore the necessity of customizing educational experiences to align with individual learner profiles. For example, research has shown that when adaptive learning systems are personalized to meet students' specific needs, there is a marked improvement in both engagement and academic performance [15]. Similarly, another study highlighted the significance of incorporating real-time feedback mechanisms, as evidenced by our Total Formative Assessments (TFA) metric, in promoting ongoing improvement and maintaining student motivation [16]. This research introduced the Dynamic Feedback-Driven

Learning Optimization Framework, which notably increased student engagement and effectiveness by delivering real-time feedback tailored to individual learning requirements. This study reinforces the critical role of advanced technology in developing more personalized and effective learning environments, emphasizing the necessity of timely feedback to sustain motivation and encourage continuous improvement. Moreover, the potential of AI-driven workplace analytics and real-time feedback systems to facilitate complex problem-solving and professional growth in situ has been highlighted [17]. This research stresses the importance of designing automated feedback systems that provide just-in-time and just-in-place support. This is vital for keeping students motivated and fostering ongoing improvement in an online learning context, where timely interventions can significantly influence student success. While the clustering approach yields valuable insights, it is crucial to acknowledge the limitations associated with relying exclusively on these quantitative metrics. Although informative, variables such as TA, TSA, TFA, AP, and FG do not encompass all the elements that affect academic success and student behavior in an online learning setting. These metrics primarily concentrate on quantitative interaction and academic performance, neglecting essential qualitative factors such as intrinsic motivation, personal and socioeconomic contexts, technological challenges, and variations in learning styles and cognitive abilities [18]. Furthermore, the current analysis fails to account for significant variables such as social support and self-efficacy, vital for comprehending how students navigate academic challenges. The literature has extensively discussed these factors as fundamental components of student success. For instance, one study emphasizes the influence of self-efficacy on students' motivation and persistence [19], while another highlights the critical role of social support in retaining students within academic programs [20]. The exclusion of these factors presents an opportunity for further refinement of student profiles, which could enhance the development of adaptive pathways that more effectively address the nuanced needs of diverse student populations. By integrating variables such as social support, self-efficacy, and learning styles, among others, into future analyses, adaptive interventions could become even more customized and impactful, ultimately improving their effectiveness in supporting the academic success of all students. Finally, table 1 shows how these findings could inform the creation of customized learning paths that cater to individual student profiles, distinguishing between high and low levels of engagement across different metrics.

Table 1: Customized learning paths based on student engagement metrics

	High level	**Low level**
Total Access to Online Content (TA)	To maintain their interest and stimulate their learning, they could be offered additional, more advanced material or optional challenges.	To make content accessible, automatic reminders, capture recurring doubts, personalized tutoring sessions, or more accessible materials (such as short videos or summaries) could be created.

	High level	Low level
Total Synchronous Activities (TSA)	They could benefit from pathways that include more live interaction opportunities, provide advanced challenges, such as implementing design patterns or utilizing interfaces and inheritance in projects.	Pathways could be designed to offer more asynchronous content, send automatic reminders, offer concise visual summaries of key concepts (like UML diagrams), or short explanatory videos.
Total Formative Assessments (TFA)	They may benefit from pathways that include more dynamic, specific and detailed formative assessments and advanced feedback to continue improving in shorter times, design assessments involving real-world scenarios, such as creating OOP-based systems for case studies.	They may require more straightforward or segmented assessments, with immediate and personalized feedback options, provide simpler exercises with step-by-step guidance to practice core concepts like encapsulation and class design, to motivate their participation and ensure their understanding.
Average Posts in Online Forums (AP)	They could be encouraged to engage in collaborative and discussion activities, encourage debates on optimal approaches to problem-solving or the use of design patterns, that exploit their willingness to interact with others.	They could benefit from activities that allow individual or anonymous participation in forums, introduce guided question forums and individual tasks to encourage reflection rather than social interaction.
Final Grade (FG)	They could receive more advanced learning paths or additional challenges to deepen their knowledge, Offer advanced supplementary materials, like working with external libraries or OOP applications for complex APIs.	They could receive additional support, provide tutoring sessions or targeted exercises addressing weak areas, such as error handling or method design.

Conclusions

This study addresses the question: What are the student profiles within an online OOP programming course designed for engineering careers? To achieve this objective, a clustering analysis was conducted utilizing historical data from the learning management system (LMS) that implements the instructional design of an introductory programming course. The analysis involved techniques for feature selection, standardization, and dimensionality reduction to ensure a robust clustering process. The findings revealed the emergence of three distinct clusters, each characterized descriptively. While these clusters offer significant insights into student behaviors and performance, the analysis is constrained by its exclusive reliance on a limited set of quantitative variables, which may neglect critical qualitative aspects such as student motivation, learning preferences, and socio-economic factors. As a result, the profiles created may not adequately represent the diverse needs of the student body, potentially hindering the effectiveness of adaptive learning pathways. Future research should aim to overcome these limitations by integrating a wider variety of variables to present a more comprehensive understanding of student profiles. Furthermore, investigations should concentrate on enhancing learning outcomes by pinpointing specific types of content and activities that foster greater engagement and exploring the reasons behind low participation in formative assessments and discussion forums. Developing targeted interventions for cluster 2 to boost their engagement and academic performance is also recommended. Subsequent steps should involve incorporating a flexibility engine within the LMS and adjustments to the underlying framework to facilitate adaptability in the dynamic assignment of materials, tasks, and evaluations, utilizing a more extensive cluster model encompassing a broader spectrum of student characteristics.

References

[1] S. Park, "Analysis of Time-on-Task, Behavior Experiences, and Performance in Two Online Courses With Different Authentic Learning Tasks," *The International Review of Research in Open and Distributed Learning*, 2017, doi: 10.19173/irrodl.v18i2.2433.

[2] Z. Zen, Reflianto, Syamsuar, and F. Ariani, "Academic Achievement: The Effect of Project-Based Online Learning Method and Student Engagement," *Heliyon*, 2022, doi: 10.1016/j.heliyon.2022.e11509.

[3] S. B. Eom, "Effects of LMS, Self-efficacy, and Self-regulated Learning on LMS Effectiveness in Business Education," *Journal of International Education in Business*, 2012, doi: 10.1108/18363261211281744.

[4] Y. Zhang, A. Ghandour, and V. Shestak, "Using Learning Analytics to Predict Students Performance in Moodle LMS," *International Journal of Emerging Technologies in Learning (Ijet)*, 2020, doi: 10.3991/ijet.v15i20.15915.

[5] G. Ciubotariu and L. M. Crivei, "Analysing the Academic Performance of Students Using Unsupervised Data Mining," *Studia Universitatis Babeș-Bolyai Informatica*, 2019, doi: 10.24193/subbi.2019.2.03.

[6] R. Gopal, V. Singh, and A. Aggarwal, "Impact of Online Classes on the Satisfaction and Performance of Students During the Pandemic Period of COVID-19," *Educ Inf Technol (Dordr)*, 2021, doi: 10.1007/s10639-021-10523-1.

[7] A. Ewais and O. De Troyer, "Usability Evaluation of an Adaptive 3D Virtual Learning Environment," *International Journal of Virtual and Personal Learning Environments*, 2013, doi: 10.4018/jvple.2013010102.

[8] Y. Wang, M. Xia, W. Guo, F. Xu, and Y. Zhao, "Academic Performance Under COVID-19: The Role of Online Learning Readiness and Emotional Competence," *Current Psychology*, 2022, doi: 10.1007/s12144-022-02699-7.

[9] M. T. Alshammari, “Design and Evaluation of an Adaptive Framework for Virtual Learning Environments,” *International Journal of Advanced and Applied Sciences*, 2020, doi: 10.21833/ijaas.2020.05.006.

[10] C. Guevara, J. Aguilar, and A. González-Eras, “The Model of Adaptive Learning Objects for Virtual Environments Instanced by the Competencies,” *Advances in Science Technology and Engineering Systems Journal*, 2017, doi: 10.25046/aj020344.

[11] N. Vaughan, B. Gabrys, and V. N. Dubey, “An Overview of Self-Adaptive Technologies Within Virtual Reality Training,” *Comput Sci Rev*, 2016, doi: 10.1016/j.cosrev.2016.09.001.

[12] Y. C. Lin, S. Wang, and Y. Lan, “The Study of Virtual Reality Adaptive Learning Method Based on Learning Style Model,” *Computer Applications in Engineering Education*, 2021, doi: 10.1002/cae.22462.

[13] D. Yang, S. Baldwin, and C. Snelson, “Persistence Factors Revealed: Students’ Reflections on Completing a Fully Online Program,” *Distance Education*, 2017, doi: 10.1080/01587919.2017.1299561.

[14] C. Wladis, K. M. Conway, and A. C. Hachey, “The Online STEM Classroom—Who Succeeds? An Exploration of the Impact of Ethnicity, Gender, and Non-Traditional Student Characteristics in the Community College Context,” *Community Coll Rev*, 2015, doi: 10.1177/0091552115571729.

[15] H. Peng, S. Ma, and J. M. Spector, “Personalized adaptive learning: an emerging pedagogical approach enabled by a smart learning environment,” *Smart Learning Environments*, vol. 6, no. 1, p. 9, Dec. 2019, doi: 10.1186/s40561-019-0089-y.

[16] C. Song, S.-Y. Shin, and K.-S. Shin, “Implementing the Dynamic Feedback-Driven Learning Optimization Framework: A Machine Learning Approach to Personalize Educational Pathways,” *Applied Sciences*, vol. 14, no. 2, p. 916, Jan. 2024, doi: 10.3390/app14020916.

[17] M. de Laat, S. Joksimovic, and D. Ifenthaler, “Artificial intelligence, real-time feedback and workplace learning analytics to support in situ complex problem-solving: a commentary,” *The International Journal of Information and Learning Technology*, vol. 37, no. 5, pp. 267–277, Aug. 2020, doi: 10.1108/IJILT-03-2020-0026.

[18] C. Hampson, O. Conlan, and V. Wade, “Challenges in Locating Content and Services for Adaptive eLearning Courses,” in *2011 IEEE 11th International Conference on Advanced Learning Technologies*, IEEE, Jul. 2011, pp. 157–159. doi: 10.1109/ICALT.2011.52.

[19] K. M. Whitcomb, A. Maries, and C. Singh, “Progression in Self-Efficacy, Interest, Identity, Sense of Belonging, Perceived Recognition and Effectiveness of Peer Interaction of Physics Majors and Comparison with Non-Majors and Ph.D. Students,” *Res Sci Educ*, vol. 53, no. 3, pp. 525–539, Jun. 2023, doi: 10.1007/s11165-022-10068-4.

[20] S. Lakkala, A. Galkienė, J. Navaitienė, T. Cierpiałowska, S. Tomecek, and S. Uusiautti, “Teachers Supporting Students in Collaborative Ways—An Analysis of Collaborative Work Creating Supportive Learning Environments for Every Student in a School: Cases from Austria, Finland, Lithuania, and Poland,” *Sustainability*, vol. 13, no. 5, p. 2804, Mar. 2021, doi: 10.3390/su13052804.