Effect of Online and Face-to-Face Engagement and Formative Assessment Score on Flipped Programming Course Outcomes and Satisfaction

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Abstract
In recent years, the flipped classroom model has gained attention for its ability to enhance learning by combining face-to-face (f2f) interactions with online activities. This study explores how different engagement levels—both online and f2f—affect course outcomes and student satisfaction, focusing on programming courses. Using advanced techniques that is, multiple regression and classification and regression tree (CART), the research examines the impact of engagement types on course satisfaction and learning outcomes. Undergraduate level object-oriented programming and database management courses were delivered via a learning management system (LMS) using a flipped instruction model. Engagement data was collected from LMS event logs, and satisfaction was assessed as a usability measure using the System Usability Scale (SUS). Engagement metrics and variables were derived from the raw data for analysis. Regression analysis demonstrated that perceived usability could be predicted by engagement data, accounting for 45% of the variance. Additionally, classification results identified online engagement as the most critical factor influencing student success. The research also highlighted the importance of formative assessment scores and f2f interactions, that is, completing lab assignments, in determining course outcomes. This study underscores the complementary roles of f2f and online activities in flipped classrooms. It provides strategic insights into designing more effective LMS-supported courses by emphasizing the need for balanced engagement strategies. These findings can guide educators in leveraging both engagement types to maximize student satisfaction and success in blended learning environments.

Keywords: Flipped classroom, programming courses, decision tree, hierarchical clustering.

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E-learning is defined as an internet-based instructional method in which content is delivered electronically, either partially or entirely, via web browsers, the Internet, multimedia platforms such as CD-ROMs and DVDs, cloud-based platforms, or dedicated application software (Lew et al., 2019; Riahi, 2015). Frequently supported by learning management systems (LMS), which enable the creation, management, and delivery of course materials worldwide (Turnbull et al., 2022), e-learning has reshaped traditional educational paradigms. The primary challenge for designers and human–computer interaction specialists is to develop tools that effectively engage novice learners and support their distance learning experiences (Ardito et al., 2006). Engagement is widely regarded as a fundamental determinant of learning outcomes, instructional quality, and student satisfaction (Fisher et al., 2018; Lai et al., 2021), and its enhancement is essential across traditional classrooms, e-learning platforms, and LMS-supported flipped classrooms.

Flipped Learning, in particular, has emerged as an effective pedagogical model, defined as the relocation of direct instruction from the group learning space to the individual learning space, while class time is transformed into a dynamic and interactive environment where educators guide students in applying concepts and engaging creatively with the subject matter (Flipped Learning Network, 2014). This approach has proven especially effective in programming education, where problem-solving and practice-based learning are essential (Almassri & Zaharudin, 2023; Karabulut-Ilgu et al., 2018). Although engineering and applied disciplines emphasise problem-solving, theoretical knowledge remains indispensable, and the flipped model has been suggested as an effective means to address theoretical requirements while freeing class time for practical application (Karabulut-Ilgu et al., 2018).

In a flipped classroom (FC) model, students interact with instructional content, commonly through lecture videos, outside of class, while class time is dedicated to hands-on activities and practice. This approach has proven particularly beneficial in programming education, where complex concepts require iterative practice and problem-solving. The FC model promotes self-efficacy, engagement, time management, student-teacher interaction, independent access to course materials, and regulation of learning flow, enabling students to control the pace and sequence of their learning. (Chiu et al., 2023; Mohamed, 2020; Taşpolat et al., 2021). Nevertheless, challenges such as technological demands, low video completion rates, and reduced attendance persist (Taşpolat et al., 2021). In programming education, these challenges are compounded by high cognitive load (Eusoff et al., 2021), differences in learning styles, interests, and motivation (Chen & Hsu, 2022), and varying levels of computational thinking skills (Menzi Çetin, 2025). Limited laboratory hours further exacerbate these issues, underscoring the need for innovative strategies. Numerous studies have confirmed that the FC approach enhances engagement and learning outcomes in programming and computer science courses (Almassri & Zaharudin, 2023; Cassano & Di Blas, 2024; Cheng et al., 2021; Durak, 2020; Özer et al., 2018; Shaarani & Bakar, 2021). Still, low engagement and high dropout rates continue to negatively influence course success (Malkoç et al., 2024), making student engagement a central issue for the effectiveness of FCs (Lai et al., 2021).

Engagement in LMS-delivered flipped classrooms is closely tied to student satisfaction and acceptance. The usability of LMS platforms is a decisive factor in overcoming barriers such as techno-tolerance and low engagement, making intuitive design and interactivity crucial for sustaining participation (Almusharraf, 2024). Engagement, as a key indicator of user behaviour in virtual task-oriented learning environments, is often measured through activity tracking, including downloads, clicks, shares, and task completion

(Morrison & Doherty, 2014; Wiebe et al., 2014). Prior research has established a strong connection between engagement and usability: Lee and Koubek (2010) found that system use significantly influences perceived usability, aesthetics, and user preferences; Harrati et al. (2016) showed that engagement metrics such as task duration and number of clicks play a crucial role in shaping usability perceptions, and Cao et al. (2019) concluded that usability evaluations differ according to the level of user engagement. Within e-learning environments, both usability and engagement directly affect learning performance (Dahleez et al., 2021).

The System Usability Scale (SUS) has been widely adopted as a reliable tool for evaluating the perceived usability of information systems (Brooke, 1996), and it plays a critical role in e-learning research. Effective usability fosters positive human–computer interaction and engagement (O'Brien & Toms, 2010; 2013), while empirical evidence shows that usability influences LMS usage patterns and user satisfaction (Orfanou et al., 2015; Pan et al., 2024). Notably, Orfanou et al. (2015) reported a significant correlation between SUS scores and frequency of LMS use. Some studies have shown that SUS can be integrated with broader models such as the Technology Acceptance Model (TAM) and Task-Technology Fit (TTF). For example, research during the COVID-19 shift to online learning found that perceived satisfaction positively influenced system usability (measured with SUS), supporting a framework that links usability, acceptance, and satisfaction (Chuenyindee et al., 2022). This demonstrates the academic validity of using SUS to assess course satisfaction in LMS contexts. In this regard, machine learning methods offer new opportunities to predict satisfaction based on engagement metrics and to identify LMS-related variables that shape student achievement. The present study therefore aims to examine the interrelationships among satisfaction, engagement, and other process data. The focus is on using machine learning techniques to predict usability and analyse achievement outcomes. In an LMS-based FC for programming courses, factors affecting success and satisfaction were investigated to overcome previously identified difficulties with this model and increase engagement. As engagement is a critical factor in the model's success, it was addressed multidimensionally in this study. Metrics relating to student participation in online sessions and laboratory hours were analysed to gain a better understanding of programming course outcomes (i.e. pass or fail) and to gain insight into student engagement.

Theoretical Framework

LMS and Data Analytics

Analytics are used to store low-level user actions and log the actual use of applications or systems. LMS log data provides insights into user engagement by recording usage patterns such as login frequency, time spent online, materials accessed, and forum activity (Alshammari, 2024; Kim et al., 2023; Moubayed et al., 2020). Analytical approaches to LMS data leverage supervised and unsupervised machine learning techniques to cluster and predict student behaviours, offering actionable data to refine course design (Dobashi, 2020; Saiz-Manzanares et al., 2021). The analysis of data collected through LMS is used to improve course design and quality (Dobashi, 2020; Zilinskiene, 2022).

In flipped courses, it is critical to identify student engagement metrics that significantly affect course outcomes (Cardello, 2013; Yoo et al., 2022). Metrics such as frequency of access to course materials, submission rates, and forum participation have been found to correlate positively with academic success (Dooley & Makasis, 2020). Studies that have used LMS log data to measure student online activity have reported on metrics such as login frequency, time spent online, the number of lessons read and downloaded, the number of quizzes and assignments completed, the number of forum topics read and created, the number of views of course components, and the completeness of course materials (Alshammari, 2024; Tan et al., 2021). Repeated interactions with lecture videos and documents enhance comprehension, particularly in challenging subjects such as programming, where dropout rates are often high (Hsueh et al., 2022). This interaction data can reveal the level of student engagement in FCs supported by the LMS.

Student Engagement Level

User engagement can be defined as the quality of the user experience that characterises positive human–computer interaction. Although it is often equated with user satisfaction, the concept extends beyond this (O'Brien & Toms, 2010). The aim of developing interactive systems in many disciplines is to create engaging experiences (O'Brien & Toms, 2010). In online learning environments, engagement is a reliable indicator of learning outcomes, regardless of the type of interaction (Doo & Kim, 2024).

The term "engagement level" refers to the frequency with which an event or action relevant to a user's interaction experience occurs. For instance, this could refer to a student posting to a forum or submitting an assignment (https://docs.moodle.org/401/en/Logs). User engagement level is defined as the frequency of interaction with the environment or materials, as well as the effort invested by the user (Moubayed et al., 2020). Researchers have proposed a number of engagement metrics, including the number of forum posts, content views, a binary indicator of assignment completion, total time spent and LMS visits (Kim et al., 2023; Moubayed et al., 2020). In this study, user engagement was gauged by the number of uploads, downloads, and views of course components.

Using quantitative methodologies to assess user engagement makes it possible to acquire data on user preferences, creating an opportunity to develop enhanced interactive experiences (Rosales et al., 2018). In their study, Rosales et al. (2018) identified several key parameters that could be used to assess engagement levels, including presence, interactivity, control, feedback, creativity and productivity, communication, and adaptation. Carlton et al. (2019) reported on low-level interaction data, including cursor movements and speed, keystrokes, event counts, and application-level data such as button clicks and time spent on an activity. This low-level data can provide insight into user engagement levels within virtual learning environments (Carlton et al., 2019; Ogbuchi, 2022). Existing literature includes studies that use unsupervised algorithms to categorise students according to their level of engagement. Moubayed et al. (2020), for example, identified two clusters based on engagement metric characteristics, namely interaction-related and effort-related. This study aimed to utilise LMS engagement metrics, specifically, the assignment submission rate, number of documents downloaded, number of video views, number of course and feedback views, and number of forum participations to ascertain the level of online engagement by applying unsupervised clustering techniques.

Predicting Academic Success

Predicting student academic success is a prominent area of research in virtual learning environments (Arévalo-Cordovilla & Peña, 2024; Beaulac & Rosenthal, 2019; Dass et al., 2021), as well as in FCs, with the aim of enhancing the efficiency of learning and teaching in programming education contexts (Chiu et al., 2023; Lin, 2019). Tree-based algorithms can be used to predict academic success and student dropout in an online learning environment. Numerous studies have demonstrated the suitability of these algorithms (Adnan et al., 2021; Beaulac & Rosenthal, 2019; Dass et al., 2021; Hawlitschek et al., 2020). To predict the success of incoming students and assess the efficacy of the implemented teaching model, the factors that influence success in LMS-supported FCs must be identified. Furthermore, using a decision tree to determine the most effective variable for academic achievement can provide valuable insights for the design of LMS-supported FCs.

Classification and regression tree (CART) is a supervised machine learning method designed for classification and regression tasks, which operates by iteratively partitioning the data based on specific parameters (Durak & Bulut, 2024). CART is highly interpretable and robust model for identifying key variables in case of categorical outcomes (Wang et al., 2024). By applying decision tree models, it becomes possible to identify the most influential predictors of student performance, such as login frequency, time spent on instructional videos, engagement in discussion forums, and timely submission of assignments (Alshammari, 2024; Dooley & Makasis, 2020; Tan, et al., 2021). Variable importance analysis not only highlights the relative contribution of these factors but also provides educators with actionable insights to improve instructional design in LMS-supported FCs (Fan et al., 2024). For instance, recognizing that consistent engagement with course materials is a stronger predictor of success than forum participation may guide instructors in prioritizing strategies that foster sustained interaction with core resources. Furthermore, the early detection of at-risk students through these predictive models enables the implementation of timely interventions, thereby enhancing both retention rates and overall academic achievement in programming education. In line with this, Yoo et al. (2022) demonstrated a regularization technique can successfully identify key predictors such as complete viewings of early instructional videos and repeated engagement with challenging content, enabling the detection of potential low performers as early as the first week of instruction. These advanced techniques are all effective in identifying the factors that influence success in programming courses organised in blended learning environments.

The programming course requires students to engage in abstract thinking and demonstrate an in-depth understanding of programming languages. Due to limited class time and the dual demands of learning grammatical programming concepts and completing sample applications, students may struggle to achieve the course's learning objectives (Durak & Bulut, 2024). In light of these challenges, the flipped learning approach is an effective strategy for enhancing the course's effectiveness. Nevertheless, it is vital to pinpoint the factors that indicate success by examining the data gathered via the LMS setting where the FC approach is employed.

Significance of the Study

The prediction of student success in flipped programming courses (FPCs) is a critical research area with significant implications for improving both learning and teaching efficiency. Programming education presents unique challenges, requiring students to develop abstract thinking, algorithmic reasoning, and coding skills within limited timeframes (Almassri & Zaharudin, 2023). The FC model, which shifts traditional instructional content to pre-class activities, has been proposed as a solution by optimizing in-class time for practical exercises and problem-solving (Chen & Hsu, 2022; Jung et al., 2024; Shaarani & Bakar, 2021). However, its success depends on multiple factors, including student engagement, course design, and LMS usability (Eusoff et al., 2021; Kuo & Chang, 2024; Taşpolat et al., 2021).

A central focus of this study is the classification of factors influencing student success in FPCs and the evaluation of teaching model effectiveness. Decision trees are particularly valuable in this context, as they allow for predicting academic success, identifying at-risk students, and analysing variable importance while providing visual and interpretable outputs (Adnan et al., 2021; Beaulac & Rosenthal, 2019; Dass et al., 2021; Hung et al., 2020; Lee et al., 2015; Villarrasa-Sapiña et al., 2024). These features make them powerful tools for designing actionable and adaptive instructional strategies (Hawlitschek et al., 2020).

Challenges in Programming Education

Programming courses are demanding, requiring mastery of complex grammatical and semantic structures, adaptation of knowledge to new problems, and completion of intricate coding tasks (Almassri & Zaharudin, 2023). Many students struggle to achieve learning objectives within the limited time available (Eusoff et al., 2021; Topalli & Çağıltay, 2018). To address these challenges, instructional strategies that enhance engagement and performance are essential. Online formative assessment has proven effective in laboratory-based programming and engineering courses, improving both programming skills and overall achievement (Cigdem et al., 2024; Veerasamy et al., 2020). Thus, integrating formative assessment into programming instruction represents a key pedagogical approach for fostering sustainable academic success.

Importance of Engagement and LMS Usability

Despite the advantages of the FC model, challenges such as students failing to watch pre-class videos or engage with materials can undermine this model's effectiveness (Kuo & Chang, 2024; Taşpolat et al., 2021). Enhancing course design, improving LMS usability, and promoting active engagement are therefore crucial. Evidence-based strategies include:

Universal Design for Learning (UDL): Providing content in diverse formats (text, audio, video, diagrams) and ensuring accessible navigation (Montes et al., 2024).

Self-Determination Theory: Supporting learner autonomy through options like self-paced modules or alternative assignments (Chiu, 2021).

Active Learning: Embedding interactive quizzes, simulations, and scenario-based tasks with immediate feedback, which significantly boost engagement (Li et al., 2023).

Structured Discussions: Guided prompts and graded forums to promote interaction and feedback (Lowenthal & Dunlap, 2020).

LMS Analytics: Monitoring metrics such as login frequency, time spent online, completed assignments, and forum activity to detect disengaged students and provide timely support (Alshammari, 2024; Olaleye et al., 2023; Tan et al., 2021).

The Moodle LMS employed in the present study supports student–content, student–student and student–teacher interaction through diverse materials, discussion forums, and personalized feedback. Its analytics tools further enable objective assessment of engagement and usability, providing early insights into student performance. In conclusion, this study aims to advance understanding of the factors influencing success in FPCs by integrating predictive analytics, engagement metrics, and course design principles. By identifying key variables, it contributes to the development of adaptive, engaging and effective learning environments tailored to the challenges of programming education.

Prior Work on LMS Analytics

Due to the performance requirements and time constraints in programming courses, Hawlitschek et al. (2020) recommended analysing some process data, i.e. error and success count in the programming tasks and task delay (the time between start of the exercise and the first-time students logged into the system to work at the task) to predict the dropout rate. They used the J48 decision tree algorithm to predict early and late dropouts. In the prediction of early and late dropouts, task delay was the most significant predictor, followed by error rate in the submission of coding tasks. Hung, et al. (2020) classified LMS interaction data to predict student success in a flipped programming course; they also conducted hierarchical clustering method to reveal behavioural patterns based on the LMS metrics. They predicted the student dropout rate using the decision tree algorithm with an accuracy rate of 0.89 along with logistic regression and random forest. They analysed the LMS data such as assignment submission status, number of clicks, exam and process scores, and forum posts, and clustered students' learning behaviour based on the dimensions of the learning mode questionnaire: active, regular, on-demand, and negative learning. The study revealed that different learning modes had different learning behaviours, i.e. active learners preferred question and answer activities and forums, while regular learners used weekly materials and submitted assignments on time.

Studies show that in similar applications, students' online interaction behaviour is influenced by their previous programming experience and learning preferences. In addition to learner characteristics, the perception of usability or satisfaction with the system is considered in this study as a factor influencing the success of the programming course. Another factor, the result of the formative assessment, shows the learner's performance score in relation to the learning process. Although Cheng, et al. (2021) showed the positive effect of formative assessment in a flipped programming course, there is not enough evidence about FPCs. In this study, tree-based techniques are applied to model the role of the mentioned factors on the programming course outcomes. Thus, it will provide a general overview of the factors related to the applied model.

Aim of the Study

The focus of this study is to create a decision tree model that categorises students based on their course outcomes (i.e., whether they pass or fail the course) and to determine the significant variables affecting these outcomes in a flipped delivery method, particularly regarding online and f2f engagement. Moreover, the study seeks to examine the influence of course design satisfaction on online engagement. Metrics associated with online engagement were analysed using multiple regression analysis, revealing the most predictive metrics in terms of course satisfaction.

The course outcomes of two programming courses, object-oriented programming and database management, were taken as "passed" and "failed" from the relevant course instructor page in the university's student information system and then binary coded as "1" and "0". The courses were delivered using the FC method, and the online sessions of the courses were conducted through Moodle LMS, an open-source e-learning environment. The LMS was also used during the laboratory sessions of the courses, during which students were asked to upload their in-class assignments to the relevant task on the LMS. While LMS log data was used to reveal both online and f2f engagement, course satisfaction was assessed through the System Usability Scale. By analysing the data obtained, answers were sought to the following questions:

- RQ1: How does course design satisfaction relate to online engagement?

- RQ2: What factors are more effective in predicting students' programming course outcomes?

CART enables interpretable prediction of student outcomes through rule-based classification, while variable importance analysis highlights the relative contribution of predictors, together providing both explanatory and predictive insights.

Method

Participants

The study was conducted in the Management Information Systems department at a public university in Turkey, in two compulsory second-year programming courses: Object-Oriented Programming (n = 62) and Database Management (n = 96). A total of 158 students (68 female and 90 male) who were enrolled on the courses participated. Both courses were delivered via a learning management system (LMS) using a flipped instruction model. Following the introductory "Algorithm and Programming" course in the first year, these courses are intensive, combining theoretical knowledge with practical application. The Object-Oriented Programming course covers key concepts such as inheritance, polymorphism and encapsulation, while the Database Management course covers the entity-relationship model and normalisation. In order to meet the learning objectives, students are expected to integrate theoretical principles with practical problem-solving in software development.

Data Collection

Course Delivery and LMS Activities

The Moodle LMS was installed on a remote web server with the objective of facilitating the delivery of online course sessions in an asynchronous manner. Furthermore, the courses were conducted in the computer laboratory during the scheduled f2f class hours. In the online sessions, students were required to view the lecture videos that had been previously created by the course instructor. In addition to the videos, the instructor prepared and uploaded lecture notes and worksheets. In the discussion forum, students were asked to share suggestions for a problem solution and to participate in question and answer (q & a) activities. Formative, process-oriented assessment was utilized to encourage student participation in the courses and deployed through LMS tools both in online and f2f sessions. Formative assessment is a process-oriented method of evaluation that considers assignments, student reflections, q & a sessions, and other observations by teachers regarding the effectiveness of learning (Dixson & Worrell, 2016). In this study, formative assessment scores were extracted from LMS log data and derived from two categories of course assignments: online and f2f. The f2f assignments were administered during laboratory sessions, whereas the online assignments were assigned following the viewing of instructional videos. All submitted tasks were uploaded to the LMS and subsequently evaluated and graded by the course instructor. Along with this score (*formative score*), other engagement data was obtained from the system event logs stored in the server database using Structured Query Language (SQL) queries. Engagement metrics are illustrated in Table 1.

Table 1

Engagement Metrics and Definitions.

Metric	Definition
Assignment submission	The binary statement of submission status of the assignments
Num. of document downloads (Dd)	The total number of downloaded documents of each student from the LMS server
Num. of video views (Vv)	The total number of times each student has watched the videos in the system
Num. of forum posts (Fp)	Active actions in the discussion forum, i.e., create a topic and write comments under an existing topic.
Num. of course views (Cv)	Total number of visits of each student to the course pages
Num. of feedback views (Fv)	Total number of views of feedback on assignment submissions or forum comments submitted by the course instructor.
Formative assessment score (Formative_score)	Sum of students' process scores from online and lab assignments.
Online engagement level (Online_eng_level)	Student's activity level in online sessions obtained by clustering analysis.
F2f engagement (Lab_assn%)	The percentage of tasks that have been completed during lab sessions.

Course Design Satisfaction

The course design satisfaction was assessed utilising the 10-item System Usability Scale (SUS), a 5-point Likert scale comprising statements that ranged from *strongly disagree* (value 0) to *strongly agree* (value 4). The questionnaire was added to the LMS using a plug-in and administered. The SUS score was calculated using the equation (Equation 1) proposed by Harrati et al. (2016).

$$Perceived\_Usability = 2.5x[\sum_{n=1}^{5}(S_{2n-1} - 1) + (5 - S_{2n})] \qquad \text{(Equation 1)}$$

In Equation 1, the variable *S* represents the rating of the i^{th} item. The SUS score ranges from 0 to 100 points, with a higher score indicating greater user satisfaction. The data underwent pre-processing to guarantee data normalisation and standardisation, and an outlier analysis was conducted. Following this, the number of observations in the data set was reduced from 158 to 150. To address the issue of missing values, the mean of each attribute was calculated and then imputed with the assistance of pertinent techniques from the Python Scikit-learn library.

Data Analysis

Preprocessing and Engagement Metrics

The system logs indicate whether each student has either completed or not completed the assigned tasks for each course. Pre- and in-class assignments were labelled in the LMS and the percentage of them submitted was calculated separately and labelled as online assignment submission rate (Online assn%) and lab assignment submission rate (Lab_assn%). Based on the online engagement metrics, clustering analysis was used to determine the level of student engagement in the online sessions. These engagement patterns also provide information about the level of student pre-class activity. The interaction amounts for all activities were initially integer values. After missing data analysis, they were converted to decimal values. Python machine learning libraries were used to process and analyse the data. In addition to the data pertaining to engagement, the responses collected via the SUS questionnaire, and the formative assessment scores were also utilised in the analyses.

Online Engagement Level

To reveal online engagement level, K-means clustering was utilized on the online engagement data. K-means is a widely used unsupervised machine learning algorithm that partitions a dataset into *k* distinct clusters by minimizing intra-cluster variance (MacQueen, 1967). Each cluster is defined by a centroid, which represents the mean of the data points assigned to that cluster. The algorithm iteratively assigns each data point to the nearest centroid based on a predefined distance metric, commonly the Euclidean distance, and updates the centroids by computing the mean of all points in each cluster. This process continues until convergence is achieved, typically when the assignments no longer change or the reduction in the cost function falls below a threshold (Jain, 2010). The objective function minimized by the algorithm is the sum of squared distances between each data point and its associated cluster centroid. Since each engagement metric was coded as it showed the amount of engagement, the outcome of clustering points to the engagement level of students. Cluster centres were calculated with the help of an unsupervised weighting function; the *silhouette index*, so the dataset was not divided into train and test parts, since the training set is not required to (Shutaywi and Kachouie, 2021). The K-means clustering analysis yielded two distinct groups of students, characterised by varying levels of engagement. The clusters obtained according to the values of the metrics are labelled as low and high engagement. Figure 1 illustrates the clustering performance for 2, 3, 4 and 5 clusters:

Figure 1

Silhouette Analysis for 2,3,4 and 5 Clusters.

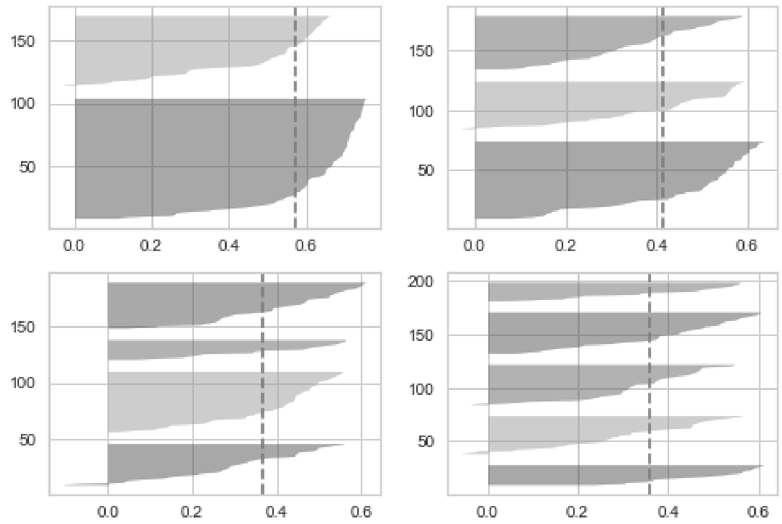


Figure 1 illustrates the Silhouette plots, which are employed for the comparative analysis of cluster centres. The calculated Silhouette coefficients (s_j) were 0.571 which has the highest value for 2 clusters. Table 2 presents the mean value of the centroid means for each metric:

Table 2

Centroid Means for Clusters

Metric	low-level	high-level
Online assn%	50.21	52.86
Dd	2.81	3.32
Vv	4.24	5.46
Fp	8.58	11.27
Cv	46.04	167.32
Fv	7.11	7.94

<u>Multiple Regression Analysis</u>

To examine the relationship between course design satisfaction and online engagement metrics, a multiple linear regression analysis was conducted using Python libraries. The dataset was divided into training and testing sets in an 80:20 ratio. The model included all engagement metrics as predictor variables and perceived usability (SUS score) as the outcome variable. To evaluate the significance of each engagement metric, backward elimination was applied with a threshold of $p > 0.01$ for removal. The final multiple regression model was represented by the Equation 2:

$$Satisfaction = Intercept \pm \beta i(\text{Online\_assn\%}) \pm \beta i\,(\text{Dd}) \pm \beta i\,(\text{Vv}) \pm \beta i\,(\text{Fp}) \pm \beta i(\text{Cv}) \pm \beta i\,(\text{Fv}) \quad \text{(Equation 2)}$$

Before proceeding with the analysis, the assumptions for multiple linear regression were tested. To address multicollinearity, the variance inflation factor (VIF) was calculated, yielding a value of 1.946, which is within acceptable limits. Additionally, the Durbin-Watson statistic was computed to assess autocorrelation, and the results confirmed no significant autocorrelation among the predictor variables.

Decision Tree Classification

A classification tree represents a supervised learning problem, wherein the output variable is categorical (e.g. success status) and an associated set of input variables (predictors) is provided. Decision trees are a powerful and readily interpretable classifier, whereby a set of classifiers is constructed using the training data set (Beaulac & Rosenthal, 2019). A classification and regression tree (CART) is a binary tree algorithm, wherein each node has only two child nodes. CART employs the Gini index as a splitting criterion. This implies that the expected error is that of randomly classifying each item according to the probability distribution of class membership within each subset (Lee et al., 2015). The Gini index is calculated using the following formula in Equation 3:

$$Gini(X_i) = \sum_{y \epsilon Y} p_{iy}\left(1 - p_{iy}\right) = 1 - \sum_{y \epsilon Y} p_{iy}^2 \qquad \text{(Equation 3)}$$

As in the Equation 3*,* *Xi* represents the distribution of a variable pertaining to a specific group*.* *Y* represents the set of values that the variable in question can assume. In the equation, p_{iy} represents the probability that a sample in group *Xi* falls into category *Y.* The *Gini* coefficient was calculated for each attribute sub-branch, with the result being a division of the nodes into two value ranges, namely “Passed” and “Failed.”

Variable importance analysis: In cases where the predictors exhibit disparate natures, the Gini measure has been observed to overestimate the importance of continuous variables (Storbl et al., 2007). This is particularly pertinent in the context of the dataset under consideration, which encompasses a range of mixed-typed values. Considering this, the recommendation put forth by Beaulac and Rosenthal (2019) is to employ a permutation decrease in importance as a benchmarking input variable. Permutation feature importance is a technique for inspecting non-linear estimators (Breiman, 2001). It involves randomly shuffling the values of a single predictor and observing the resulting decrease in model accuracy. This allows the degree to which the model relies on the predictor in question to be determined. The algorithmic procedure underlying this technique is as follows:

1. Construct a tree model *DT* using training and test data (*D*)
2. Compute the reference score (*rs*) of the *DT* on *D* (accuracy of *DT*)
3. For each feature *j* (column of *D*):
   - For each repetition *k* in 1, …, *K*:
     - Randomly shuffle column *j* of *D* to generate a corrupted version of the data, $\check{D}_{k,j}$
     - Compute the score s_{kj} of *DT* on $\check{D}_{k,j}$
   - Compute importance i_j for feature *fj* defined as follow equation:

$$i_j = s - \frac{1}{K}\sum_{k=1}^{K} s_{k,j} \qquad \text{(Equation 4)}$$

A permutation decrease in importance was implemented on the existing classifier, utilising the Gini impurity method. The ranking of features was then determined by the provided equation in Equation 4. The results were visualised using Python libraries.

Results

Result of Regression Analysis

The one-way analysis of variance demonstrated that the SUS score exhibited a statistically significant difference in relation to the level of engagement at 0.05 significance level (F=8.59; p=.003). Considering previous research that suggests SUS is a measure of user perception, and not actual usability (Drew, et al., 2018), highly engaged students found the usability of course design within acceptable limits (Mean SUSs= 68.38), while low-engaged students found it not acceptable (60.49) according to the scale interpretations (McLellan, et al., 2012). On the basis of this finding, it can be assumed that a low level of engagement in online course sessions is associated with a low level of satisfaction with the course design. The results of the multiple regression model with backward elimination method indicated that four of the six attributes with a significance level of less than 0.01 were included in the model: online assignment submission rate, number of video views, number of forum posts, and number of course views. The prediction model indicated that the specified metrics contributed significantly to the model (F=42.58, p<.001). The results of the prediction model are presented in Table 3.

Table 3

*Regression Model for Prediction of Perceived Usability**

	b	SE b	β*	RMSE	t	*p*
Constant	39.89	2.39		0.437		
Online_assn %	0.194	0.046	0.181		4.47	.000
Vv	0.911	0.253	0.632		3.59	.000
Fp	0.407	0.113	0.420		3.59	.000
Cv	0.046	0.013	0.044		3.64	.000

* $R^2=.451$, $Adj.R^2=.428$, $F=19.56$, $p<.001$

Students' online activities other than downloading documents and viewing feedback positively predicted their satisfaction with the system. On the other hand, students with low engagement did not find the system useful. This is an indication that the system has some usability issues from a subjective point of view, which may have an impact on online engagement.

Results of Classification Analysis

The initial decision tree model exhibited an accuracy of 87% and was constituted by a 9-level tree structure. To enhance the model's performance, the cost-complexity pruning process, as proposed for the CART algorithm (Lee et al., 2015), was implemented. The process yielded a confidence coefficient (α) value of 0.0173, which was then provided as a tuning parameter to the model to achieve the maximum accuracy rate. The newly constructed tree model, comprising four levels and a reduced number of rules, exhibited an enhanced accuracy rate of 89%. Table 4 shows the statistics for the components of the pruned classification tree.

Table 4

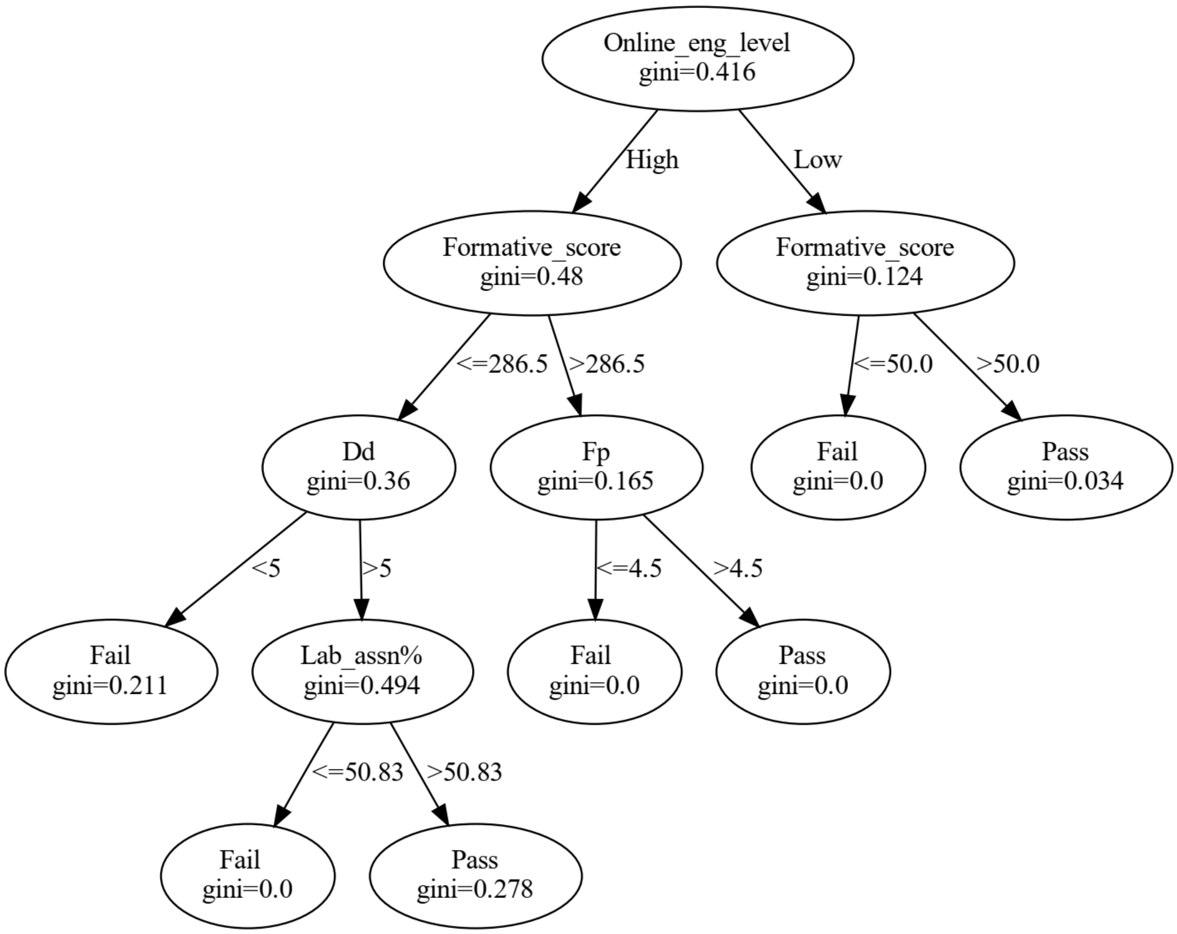
Mean Values of Classifiers for Passed and Failed Students

Metric	Passed (N=105)	Failed (N=45)	Overall (N=150)	p^*
Dd	3.38 (2.9)	2.11 (2.23)	3.0 (2.77)	0.01
Fp	10.38 (8.33)	7.68 (6.51)	9.57 (7.9)	0.055
Lab_assn%	58.94 (22.01)	43.71 (21.32)	54.37 (22.8)	<.001
Formative_score	266.45 (125.21)	135.98 (102.78)	227.3 (132.9)	<.001

**Significance level of t-test for compare failed and passed students.*

T-test results showed that there were significant differences between the mean scores of passing and failing students in terms of Lab_assn% and Formative_score. In terms of the metrics in question, those who scored above the class average are successful students in the course. The structure of the tree is shown in the Figure 2:

Figure 2 *Post-Pruned Decision Tree Model for Course Result Prediction*



In the Figure 2, four-level tree illustrated the course success status at leaf nodes, while online engagement level is at the root node. The error matrix and the model performance values for the pruned tree is shown in Table 5:

Table 5

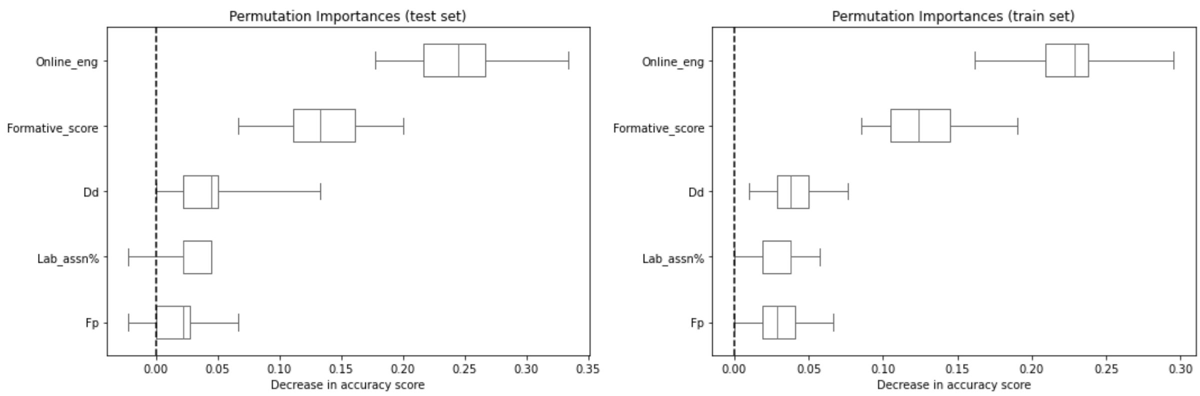
Error Matrix and Model Performance

	Actual 1	Actual 0	Precision
Predicted 1	28	3	0.93
Predicted 0	2	12	0.80
Recall	0.90	0.86	
Accuracy	0.89		

As illustrated in the Table 5, the model was classified according to the input variables based on the course achievement, with an accuracy rate of 89%. Other performance values are F-1 score and Area Under ROC Curve (AUC) are respectively 0.92 and 0.88, the mean squared error of the classification model is 0.11. In terms of variable importance analysis as shown in the Figure 3, online engagement level is the most influential factor on the model accuracy, followed by the formative assessment score, number of document downloads (Dd), laboratory assignment submission rate (Lab_assn%) and number of forum posts (Fp). As a result of the variable importance analysis shown in the Figure 3, the variables (Online_assn%, Vv, Cv, Fv, As_sub_time) that did not have a significant effect on the accuracy of the model were removed from the analysis and the model was reconstructed.

Figure 3

Boxplot for Permutation Decrease Importances on Test and Train Data



A variable importance analysis revealed that the online activity level was the most significant classifier. The following variables were identified as having a notable impact: formative assessment score, number of document downloads, laboratory assignment submission rates and the number of forum posts. Alshammari (2024) reported similar classifiers (average submission rate and average content access) on student interaction at a lower DT model accuracy. However, contrary to the relevant research findings (Adnan et al., 2021; Sáiz-Manzanares et al., 2021), number of feedback views did not demonstrate a substantial effect on model accuracy. The comprehensive decision rules for course success are presented in the Table 6:

Table 6

Decision Tree Rules for Passed and Failed Students

Node	Rule	Class	N.of cases
5	Online_eng_level=Low and Formative_score ≤ 50.0	Fail	3
6	Online_eng_level=Low and Formative_score > 50.0	Pass	57
7	Online_eng_level=High and Formative_score ≤ 286.5 and Dd≤ 5	Fail	25
9	Online_eng_level=High and Formative_score >286.5 and Fp≤4.5	Fail	1
10	Online_eng_level=High and Formative_score >286.5 and Fp>4.5	Pass	10
11	Online_eng_level=High and Formative_score ≤ 286.5 and Dd>5 and Lab_assn% ≤ 50.83	Fail	3
12	Online_eng_level=High and Formative_score ≤ 286.5 and Dd>5 and Lab_assn% >50.83	Pass	6

The rules extracted from the decision tree provided insights into the implementation of the FPC model. Along with online engagement level, formative assessment scores were an important factor in course outcomes. For students with low online engagement, those who scored above a certain number of points on course assignments (both pre-class and lab) were able to pass the course. In addition to high online engagement, students with above-average process performance, as well as students with a certain level of active participation in the discussion forum and students with a high lab task completion rate (>50.83) have positive course outcomes.

The overall results of the analysis have led to the formulation of several rules that are conducive to success in the FPC course. These rules include a greater degree of interaction with the course elements and higher level of formative assessment score (process performance) are associated with positive outcomes in the programming courses. Course design satisfaction supports course outcomes as it is highly correlated with online interactions.

Discussion

Based on the results of variance and regression analysis, it can be hypothesized that higher satisfaction levels lead to greater engagement with the system. In response to the first research question, it was found that students' satisfaction with the design of the online course is related to indicators of online engagement. In other words, course design satisfaction is predicted by engagement metrics: assignment submission rate, number of video views, forum posts and course views. In terms of system usability, students who found the system useful interacted more with the course elements mentioned. In the flipped classroom, a significant part of the course content is delivered through videos. The ease of accessing the course videos and using other elements (assignments and discussion forum) on the page is due to the simple and clear design of the system and increases student interaction. These student-content interactions, along with student-student and student-instructor interactions facilitated through discussion forums, were strongly correlated with system satisfaction in similar learning environments (Pham, 2025). Research has consistently shown the positive impact of system satisfaction on engagement in learning environments. For example, Ramaswami et al. (2023) demonstrated that students found the LMS dashboard intuitive and easy to use, contributing to increased engagement. Moreover, perceived usability has been identified as a critical factor in student adoption, satisfaction, and continued participation in e-learning systems and LMSs (Chu et al., 2020; Chuenyindee et al., 2022; Dutta et al., 2021). It has also been directly linked to improved performance and learning effectiveness in LMSs (Orfanou et al., 2015).

The second research question concluded that the level of online engagement is the most influential factor in programming course outcomes, followed by formative assessment scores, the number of documents downloaded, the rate at which laboratory assignments are submitted, and the number of forum posts. While online engagement remains a critical component of success in flipped learning environments, the present study underscores the significant contribution of face-to-face (f2f) engagement, particularly in the context of completing laboratory assignments. Flipped learning models are designed to foster deeper cognitive engagement with course content (Shen, 2024; Smallhorn, 2017; Talan & Gülseçen, 2019), yet the findings suggest that in-person interactions with laboratory assignments play a notable role in promoting overall academic achievement. Some research findings also support the view that the f2f course format, with its interactive features, remains the preferred option for demanding and compulsory courses (Wladis et al., 2025). These two forms of engagement, online and f2f, address different dimensions of student engagement, and together they create a complementary and mutually reinforcing learning experience. This relationship can be meaningfully interpreted through the lens of the ICAP (Interactive, Constructive, Active, Passive) framework proposed by Chi and Wylie (2014). The ICAP framework posits that learning outcomes improve progressively as student engagement shifts from passive reception to interactive participation. In this context, laboratory activities, which emphasize hands-on practice and motor behaviours, align with *active* engagement, while dialogues, whether conducted in person or through online platforms, embody *interactive* engagement. The integration of these modalities within a flipped learning approach reflects a deliberate alignment with the ICAP model, facilitating deeper learning and higher academic performance through the combination of active and interactive learning strategies.

In terms of feature importance, online activity level emerged as the most critical predictor of course success after formative assessment scores. Formative assessments, which evaluated both laboratory and online assignment submissions, had a significant influence on programming course outcomes. Similarly, Wang (2017) found that formative assessment results strongly impacted achievement in flipped classrooms. Additionally, formative assessments and feedback have been shown to enhance student engagement and satisfaction (Cassano & Di Blas, 2024; Cigdem et al., 2024; Ziegenfuss & Furse, 2021). In this study, short feedback was provided to students, and the number of times they viewed the feedback (Fv) was analysed. While feedback was not directly linked to achievement or satisfaction, it contributed to overall online activity levels. As noted in related studies, formative, process-oriented assessments and remote feedback positively impact programming course success (Adnan et al., 2021; Alshammari, 2024; Veerasamy et al., 2020). Additionally, metrics such as assignment submission rates and the number of downloaded lecture materials were identified as significant predictors in programming education (Alshammari, 2024; Hung et al., 2020).

The number of forum posts and document downloads were found to be the most critical indicators of online and pre-class engagement, respectively. Discussion forums became particularly engaging when teachers actively guided discussions, demonstrating that these platforms support knowledge construction rather than merely social interaction (Xie et al., 2024). Contrary to some studies (Hsueh et al., 2022; Shen, 2024) but aligned with Beatty et al. (2019), the number of video views was not a significant predictor, while document downloads played a more substantial role in the blended learning model. Laboratory assignment submission rates also significantly influenced programming course outcomes, underscoring the importance of f2f, in-class engagement. While online pre-class engagement, especially assignment submissions, was associated with better programming lab performance (Tran et al., 2024), higher engagement in lab assignments was particularly impactful in this study.

Student engagement is a crucial component of quality higher education, directly linked to academic success, positive educational outcomes, and satisfaction (Fanshawe et al., 2025; Fisher et al., 2018; Martinez-Carrascal et al., 2020; Tan et al., 2021). In programming courses, learning analytics can identify at-risk students in LMS-delivered courses, enabling targeted strategies to improve engagement (Adnan et al., 2021; Lu et al., 2018). While efforts to enhance engagement and achievement in programming courses through flipped learning models have been reported (Shaarani & Bakar, 2021; Durak, 2020), this study underscores the importance of perceived usability as a key factor influencing engagement and success, supported by its proposed variables and analysis approach.

Implications

Programming courses are widely regarded as some of the most challenging in higher education, often associated with the highest dropout rates (Arévalo-Cordovilla & Peña, 2024; Eusoff et al., 2021; Ruiz-de-Miras et al., 2021; Topalli & Çağıltay, 2018; Zhang et al., 2023). Given the tendency for lower success rates in such courses, process-oriented metrics, such as assignment completion rates and formative assessment scores, become critical for evaluating progress. Insights from the implementation of programming courses highlight the need for incorporating abundant practical examples and materials into course design. Additionally, formative assessments, along with fostering student-student and student-instructor interaction via discussion forums, play pivotal roles in the success of programming-focused curricula. Presenting course content and resources in a simple, intuitive manner further enhances the learning experience, creating a more user-friendly environment. These strategies collectively address the challenges of programming courses and support student success.

Limitations and Suggestions

A key limitation of this study is the relatively small sample size, which may affect the performance of the classification model. However, recent studies have shown that decision tree algorithms can perform effectively with similar sample sizes when predicting academic achievement (Hung et al., 2020; Sáiz-Manzanares et al., 2021; Villarrasa-Sapina et al., 2024). Accessing large amounts of real data in e-learning environments becomes difficult if MOOCs are not being studied and there are barriers to implementation. Consequently, the generalisability of results obtained through machine learning analyses is reduced. It may therefore be advisable to increase the volume of data by creating synthetic datasets based on the distribution of real data, thereby improving the predictive accuracy of analyses (Shabnam-Ara et al., 2025).

To improve LMS usability and foster course engagement, additional tools and plugins could be developed. For instance, integrating code editors and integrated development environments (IDEs) directly into the LMS to enable compiling and executing coding tasks within the platform could enhance functionality and support collaborative coding activities. Additionally, a video annotation plugin, as proposed by Cassano et al. (2024), could increase student engagement, encourage active participation in online sessions, and improve the overall effectiveness of instructional methods. Such innovations could significantly enhance student interaction and engagement (Gallego-Romero et al., 2020).

This study measures usability using the System Usability Scale (SUS), which evaluates user satisfaction with an information system (Brooke, 1996). While SUS is well-suited to assess user satisfaction, other usability measurement techniques focus on different aspects, such as effectiveness and efficiency. Given the critical role of user satisfaction in shaping students' learning outcomes and course evaluations in LMS contexts, as highlighted by Ramos et al. (2021), SUS was considered an appropriate tool for this study. Future research could explore alternative usability assessment methods to provide a more comprehensive evaluation of programming course design.

The scope of this study was limited to programming courses in Turkey, which may restrict how widely the findings can be generalised to other educational contexts. Nevertheless, the challenges addressed in this study, such as student engagement, perceived usability and achievement in LMS-supported flipped classrooms, are not unique to Turkey. Therefore, future research could build on this work by testing the model in diverse cultural and disciplinary contexts to enhance its external validity.

Declarations

Disclosure statement: No potential conflict of interest was reported by the author.

Ethical statement: Permission to collect data from students was approved by the Adana Alparslan Türkeş Science and Technology University Research and Publication Ethics Board (Verification code: 7HBN-VDTP-84GB).

Data availability statement: Data will be made available on reasonable requests.

References

Adnan, M., Habib, A., Ashraf, J., Mussadiq, S., Raza, A. A., Abid, M., Bashir, M., & Khan, S. U. (2021). Predicting at-risk students at different percentages of course length for early intervention using machine learning models. *IEEE Access, 9*, 7519–7539. https://doi.org/10.1109/ACCESS.2021.3049446

Almassri, M. A., & Zaharudin, R. (2023). Effectiveness of flipped classroom pedagogy in programming education: A meta-analysis. *International Journal of Instruction, 16*(2), 267–290. https://doi.org/10.29333/iji.2023.16216a

Almusharraf, A. I. (2024). An investigation of university students' perceptions of learning management systems: Insights for enhancing usability and engagement. *Sustainability, 16*(22), 10037. https://doi.org/10.3390/su162210037

Alshammari, A. (2024). Using analytics to predict students' interactions with learning management systems in online courses. *Education and Information Technologies, 29*, 20587–20612. https://doi.org/10.1007/s10639-024-12709-9

Ardito, C., Costabile, M. F., Marsico, M. D., Lanzilotti, R., Levialdi, S., Roselli, T., & Rossano, V. (2006). An approach to usability evaluation of e-learning applications. *Universal Access in the Information Society, 4*(3), 270–283. https://doi.org/10.1007/s10209-005-0008-6

Arévalo-Cordovilla, F. E., & Peña, M. (2024). Comparative analysis of machine learning models for predicting student success in online programming courses: A study based on LMS data and external factors. *Mathematics*, *12*(20), 3272. https://doi.org/10.3390/math12203272

Beatty, B.J., Merchant, Z., & Albert, M. (2019). Analysis of student use of video in a flipped classroom. *TechTrends 63*, 376–385. https://doi.org/10.1007/s11528-017-0169-1

Beaulac, C., & Rosenthal, J. S. (2019). Predicting university students' academic success and major using random forests. *Research in Higher Education*, *60*, 1048-1064. https://doi.org/10.1007/s11162-019-09546-y

Breiman, L. (2001). Random forests. *Machine Learning 45*, 5–32. https://doi.org/10.1023/A:1010933404324

Brooke, J. (1996). SUS-A quick and dirty usability scale. *Usability Evaluation in Industry*, *189*(194), 4–7.

Cao, L., Peng, C., & Hansberger, J. T. (2019). Usability and engagement study for a serious virtual reality game of lunar exploration missions. *Informatics, 6*(4), 44. https://doi.org/10.3390/informatics6040044

Carlton, J., Brown, A., Jay, C., & Keane, J. (2019). Inferring user engagement from interaction data. In *Extended abstracts of the 2019 CHI conference on human factors in computing systems* (pp. 1–6). Association for Computing Machinery. https://doi.org/10.1145/3290607.3313009

Cassano, G., & Di Blas, N. (2024). A tool to support students-to-teacher feedback in asynchronous online contexts. *IEEE Transactions on Learning Technologies*, *17*, 585–593. https://doi.org/10.1109/TLT.2023.3273109

Cassano, G., Di Blas, N., & Mataresi, A. (2024). Enhancing learning engagement in the flipped classroom using a video-annotation tool. *Electronic Journal of e-Learning*, *22*(9), 75–90. https://doi.org/10.34190/ejel.22.9.3259

Chen, H. R., & Hsu, W. C. (2022). Do flipped learning and adaptive instruction improve student learning outcome? A case study of a computer programming course in Taiwan. *Frontiers in Psychology*, *12*, 768183. https://doi.org/10.3389/fpsyg.2021.768183

Cheng, S. C., Cheng, Y. P., Huang, Y. M., & Yang, Y. (2021). Combining flipped learning and formative assessment to enhance the learning performance of students in programming. In: Y. M. Huang, C. F. Lai, T. Rocha (Eds.), *Innovative technologies and learning (ICITL 2021). Lecture notes in computer science: Vol. 13117.* (pp. 498–507). Springer, Cham. https://doi.org/10.1007/978-3-030-91540-7_51

Chi, M. T., & Wylie, R. (2014). The ICAP framework: Linking cognitive engagement to active learning outcomes. *Educational Psychologist*, *49*(4), 219–43. https://doi.org/10.1080/00461520.2014.965823

Chiu, P. S., Zhong, H. X., & Lai, C. F. (2023). Investigating the effects of a programming course using flipped learning. *Innovations in Education and Teaching International*, *60*(4), 578–90. https://doi.org/10.1080/14703297.2022.2080097

Chiu, T. K. F. (2021). Student engagement in K-12 online learning amid COVID-19: A qualitative approach from a self-determination theory perspective. *Interactive Learning Environments*, *31*(6), 3326–3339. https://doi.org/10.1080/10494820.2021.1926289

Chu, A., Biancarelli, D., Drainoni, M. L., Liu, J. H., Schneider, J. I., Sullivan, R., & Sheng, A. Y. (2020). Usability of learning moment: Features of an e-learning tool that maximize adoption by students. *Western Journal of Emergency Medicine*, *21*(1), 78. https://doi.org/10.5811%2Fwestjem.2019.6.42657

Chuenyindee, T., Montenegro, L. D., Ong, A. K. S., Prasetyo, Y. T., Nadlifatin, R., Ayuwati, I. D., Sittiwatethanasiria, T., & Robas, K. P. E. (2022). The perceived usability of the learning management system during the COVID-19 pandemic: Integrating system usability scale, technology acceptance model, and task-technology fit. *Work*, *73*(1), 41–58. https://doi.org/10.3233/WOR-220015

Cigdem, H., Ozturk, M., Karabacak, Y., Atik, N., Gürkan, S., & Aldemir, M. H. (2024). Unlocking student engagement and achievement: The impact of leaderboard gamification in online formative assessment for engineering education. *Education and Information Technologies*, *29* 24835–24860. https://doi.org/10.1007/s10639-024-12845-2

Dahleez, K. A., El-Saleh, A. A., Al Alawi, A. M., & Abdel Fattah, F. A. M. (2021). Student learning outcomes and online engagement in time of crisis: The role of e-learning system usability and teacher behavior. *International Journal of Information and Learning Technology, 38*(5), 473–492. https://doi.org/10.1108/IJILT-04-2021-0057

Dass, S., Gary, K. & Cunningham, J. (2021). Predicting student dropout in self-paced MOOC course using random forest model. *Information*, *12*, 476. https://doi.org/10.3390/info12110476

Dixson, D. D., & Worrell, F. C. (2016). Formative and summative assessment in the classroom. *Theory into Practice*, *55*(2), 153–59. https://doi.org/10.1080/00405841.2016.1148989

Dobashi, K. (2020). Development of real-time learning analytics using scraping and pivot tables. In I. Nunes (Ed.), *Advances in human factors and systems interaction (AHFE 2020)* (*Advances in Intelligent Systems and Computing*, Vol. 1207). Springer. https://doi.org/10.1007/978-3-030-51369-6_42

Doo, M. Y., & Kim, J. (2024). The relationship between learning engagement and learning outcomes in online learning in higher education: A meta-analysis study. *Distance Education*, *45*(1), 60–82. https://doi.org/10.1080/01587919.2024.2303484

Dooley, L., & Makasis, N. (2020). Understanding student behavior in a flipped classroom: Interpreting learning analytics data in the veterinary pre-clinical sciences. *Education Sciences*, *10*(10), 260. https://doi.org/10.3390/educsci10100260

Drew, M. R., Falcone, B., & Baccus, W. L. (2018). What does the System Usability Scale (SUS) measure? In A. Marcus & W. Wang (Eds.), *Design, user experience, and usability: Theory and practice. DUXU 2018* (*Lecture Notes in Computer Science*, Vol. 10918) (pp. 283–294). Springer, Cham. https://doi.org/10.1007/978-3-319-91797-9_25

Durak, A., & Bulut, V. (2024). Classification and prediction-based machine learning algorithms to predict students' low and high programming performance. *Computer Applications in Engineering Education*, *32*(1), e22679. https://doi.org/10.1002/cae.22679

Durak, H. Y. (2020). Modeling different variables in learning basic concepts of programming in flipped classrooms. *Journal of Educational Computing Research*, *58*(1), 160–199. https://doi.org/10.1177/0735633119827956

Dutta, B., Peng, M. H., Chen, C. C., & Sun, S. L. (2021). Interpreting usability factors predicting sustainable adoption of cloud-based E-learning environment during COVID-19 pandemic. *Sustainability*, *13*(16), 9329. https://doi.org/10.3390/su13169329

Eusoff, R., Salleh, S. M., & Zin, A. M. (2021). Implementing flipped classroom strategy in learning programming. *International Journal of Advanced Computer Science and Applications*, *12*(10), 602–07. https://doi.org/10.14569/IJACSA.2021.0121066

Fan, Z., Gou, J., & Weng, S. (2024). A feature importance-based multi-layer CatBoost for student performance prediction. *IEEE Transactions on Knowledge and Data Engineering, 36*(11), 5495–5507. https://doi.org/10.1109/TKDE.2024.3393472

Fanshawe, M., Brown, A., & Redmond, P. (2025). Using an online engagement framework to redesign the learning environment for higher education students: A design experiment approach. *Online Learning,29*(2), pp.269–297. https://doi.org/10.24059/olj.v29i2.4447

Fisher, R., Perényi, A., & Birdthistle, N. (2018). The positive relationship between flipped and blended learning and student engagement, performance and satisfaction. *Active Learning in Higher Education*, *22*(2), 97–113. https://doi.org/10.1177/1469787418801702

Flipped Learning Network (FLN) (2014). What is flipped learning? The Four Pillars of F-L-I-P™. https://flippedlearning.org/definition-of-flipped-learning/

Gallego-Romero, J. M., Alario-Hoyos, C., Estévez-Ayres, I., & Delgado Kloos, C. (2020). Analyzing learners' engagement and behavior in MOOCs on programming with the Codeboard IDE. *Educational Technology Research and Development*, *68*, 2505–28. https://doi.org/10.1007/s11423-020-09773-6

Harrati, N., Bouchrika, I., Tari, A., & Ladjailia, A. (2016). Exploring user satisfaction for e-learning systems via usage-based metrics and system usability scale analysis. *Computers in Human Behavior*, *61*, 463–71. https://doi.org/10.1016/j.chb.2016.03.051

Hawlitschek, A., Köppen, V., Dietrich, A., & Zug, S. (2020). Drop-out in programming courses–prediction and prevention. *Journal of Applied Research in Higher Education*, *12*(1), 124–136. https://doi.org/10.1108/JARHE-02-2019-0035

Hsueh, N. L., Daramsenge, B., & Lai, L. C. (2022). Exploring the influence of students' modes of behavioral engagement in an online programming course using the partial least squares structural equation modeling approach. *Journal of Information Technology Education: Research*, *21*, 403–23. https://doi.org/10.28945/5010

Hung, H. C., Liu, I. F., Liang, C. T., & Su, Y. S. (2020). Applying educational data mining to explore students' learning patterns in the flipped learning approach for coding education. *Symmetry*, *12*(2), 213. https://doi.org/10.3390/sym12020213

Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters, 31*(8), 651–666. https://doi.org/10.1016/j.patrec.2009.09.011

Jung, J., Shin, Y., Chung, H., & Fanguy, M. (2024). The effects of pre-training types on cognitive load, self-efficacy, and problem-solving in computer programming. *Journal of Computing in Higher Education*, *37*, 809–830. https://doi.org/10.1007/s12528-024-09407-3

Karabulut-Ilgu, A., Jaramillo Cherrez, N., & Jahren, C. T. (2018). A systematic review of research on the flipped learning method in engineering education. *British Journal of Educational Technology*, *49*(3), 398–411. https://doi.org/10.1111/bjet.12548

Kim, S., Cho, S., Kim, J. Y., & Kim, D. J. (2023). Statistical assessment on student engagement in asynchronous online learning using the k-means clustering algorithm. *Sustainability*, *15*(3), 2049. https://doi.org/10.3390/su15032049

Kuo, Y.C., Chang, P.J. (2024). Flipped classroom combined with WPACQ learning mode on student learning effect - exemplified by program design courses. *Education and Information Technologies, 29*, 12621–12651 https://doi.org/10.1007/s10639-023-12384-2

Lai, H. M., Hsieh, P. J., Uden, L., & Yang, C. H. (2021). A multilevel investigation of factors influencing university students' behavioral engagement in flipped classrooms. *Computers & Education*, *175*, 104318. https://doi.org/10.1016/j.compedu.2021.104318

Lee, S. & Koubek, R. J. (2010). Understanding user preferences based on usability and aesthetics before and after actual use, *Interacting with Computers*, *22*(6), 530–543. https://doi.org/10.1016/j.intcom.2010.05.002

Lee, V. E., Liu, L., & Jin, R. (2015). Decision trees: Theory and algorithms. In C. C. Aggarwal (Ed.), *Data classification algorithms and applications* (pp. 87–120). CRC Press.

Lew, S. L., Lau, S. H., & Leow, M. C. (2019). Usability factors predicting continuance of intention to use cloud e-learning application. *Heliyon*, *5*(6), e01788. https://doi.org/10.1016/j.heliyon.2019.e01788

Li, M., Ma, S., & Shi, Y. (2023). Examining the effectiveness of gamification as a tool promoting teaching and learning in educational settings: A meta-analysis. *Frontiers in Psychology*, *14*, 1253549. https://doi.org/10.3389/fpsyg.2023.1253549

Lin, Y. T. (2019). Impacts of a flipped classroom with a smart learning diagnosis system on students' learning performance, perception, and problem-solving ability in a software engineering course. *Computers in Human Behavior, 95*, 187–196. https://doi.org/10.1016/j.chb.2018.11.036

Lowenthal, P. R., & Dunlap, J. C. (2020). Social presence and online discussions: A mixed method investigation. *Distance Education*, *41*(4), 490–514. https://doi.org/10.1080/01587919.2020.1821603

Lu, O. H., Huang, J. C., Huang, A. Y., & Yang, S. J. (2018). Applying learning analytics for improving students' engagement and learning outcomes in a MOOCs-enabled collaborative programming course. In G.-J. Hwang, H.-C. Chu, & C. Yin (Eds.), *Learning analytics* (pp. 78–92). Routledge. https://doi.org/10.4324/9780429428500

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* (Vol. 1, No. 14, pp. 281–297). University of California Press.

Malkoc, S., Steinmaurer, A., Gütl, C., Luttenberger, S., & Paechter, M. (2024). Coding decoded: Exploring course achievement and gender disparities in an online flipped classroom programming course. *Education Sciences*, *14*(6), 634. https://doi.org/10.3390/educsci14060634

McLellan, S., Muddimer, A., & Peres, S. C. (2012). The effect of experience on system usability scale ratings. *Journal of Usability Studies*, *7*(2), 56–67.

Menzi Çetin, N. (2025). A comparison of the programming-oriented computational thinking skills of engineering and nonengineering students at Turkish universities. *Computer Applications in Engineering Education*, *33*(5), e70069. https://doi.org/10.1002/cae.70069

Mohamed, A. (2020). Evaluating the effectiveness of flipped teaching in a mixed-ability cs1 course. *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education (ITICSE '2020)*, 452–458. https://doi.org/10.1145/3341525.3387395

Montes, R., Herrera, L., & Crisol, E. (2024). Moodle usability assessment methodology using the universal design for learning perspective. *arXiv preprint arXiv:2403.10484*. https://doi.org/10.48550/arXiv.2403.10484

Morrison, C., & Doherty, G. (2014). Analyzing engagement in a web-based intervention platform through visualizing log-data. *Journal of Medical Internet Research, 16*(11), e252. https://doi.org/10.2196/jmir.3575

Moubayed, A., Injadat, M., Shami, A., & Lutfiyya, H. (2020). Student engagement level in an e-learning environment: Clustering using k-means. *American Journal of Distance Education*, *34*(2), 137–56. https://doi.org/10.1080/08923647.2020.1696140

O'Brien, H. L., & Toms, E. G. (2013). Examining the generalizability of the User Engagement Scale (UES) in exploratory search. *Information Processing & Management*, *49*(5), 1092–1107. https://doi.org/10.1016/j.ipm.2012.08.005

O'Brien, H. L., & Toms, E. G. (2010). The development and evaluation of a survey to measure user engagement. *Journal of the American Society for Information Science and Technology*, *61*(1), 50–69. https://doi.org/10.1002/asi.21229

Ogbuchi, I., Kiely, E., Quigley, C., & McGinty, D. (2022, November 7–9). Exploring the use of machine learning to improve student engagement and retention. In *ICERI2022 proceedings: 15th annual International Conference of Education, Research and Innovation* (pp. 3385–3390). IATED. https://doi.org/10.21125/iceri.2022.0828

Olaleye, S., Agjei, R., Jimoh, B., & Adoma, P. (2023). Evaluation of usability in Moodle learning management system through analytics graphs: University of applied sciences teacher's perspective in Finland. *International Journal of Education and Development Using Information and Communication Technology*, *19*(3), 85–107.

Orfanou, K., Tselios, N., & Katsanos, C. (2015). Perceived usability evaluation of learning management systems: Empirical evaluation of the system usability scale. *The International Review of Research in Open and Distributed Learning*, *16*(2), 227–46. https://doi.org/10.19173/irrodl.v16i2.1955

Özer, H. H., Kanbul, S., & Ozdamli, F. (2018). Effects of the gamification supported flipped classroom model on the attitudes and opinions regarding game-coding education. *International Journal of Emerging Technologies in Learning (iJET)*, *13*(1), 109–123. https://doi.org/10.3991/ijet.v13i01.7634

Pan, Z., Biegley, L., Taylor, A., & Zheng, H. (2024). A systematic review of learning analytics: Incorporated instructional interventions on learning management systems. *Journal of Learning Analytics*, *11*(2), 52–72. https://doi.org/10.18608/jla.2023.8093

Pham, A. T. (2025). Blended MOOCs in higher education: Analyzing student interaction and satisfaction. *Contemporary Educational Technology, 17*(1), ep550. https://doi.org/10.30935/cedtech/15689

Ramaswami, G., Susnjak, T., & Mathrani, A. (2023). Effectiveness of a learning analytics dashboard for increasing student engagement levels. *Journal of Learning Analytics*, *10*(3), 115–134. https://doi.org/10.18608/jla.2023.7935

Ramos, V. F. C., Cechinel, C., Mage, L., & Lemos, R. (2021). Student and lecturer perceptions of usability of the virtual programming lab module for Moodle. *Informatics in Education, 20*(2), 297–315. https://doi.org/10.15388/infedu.2021.14

Riahi, G. (2015). E-learning systems based on cloud computing: A review. *Procedia Computer Science, 62*, 352–359. https://doi.org/10.1016/j.procs.2015.08.415

Rosales, R., Castañón-Puga, M., Lara-Rosano, F., Flores-Parra, J. M., Evans, R., Osuna-Millan, N., & Gaxiola-Pacheco, C. (2018). Modelling the interaction levels in HCI using an intelligent hybrid system with interactive agents: A case study of an interactive museum exhibition module in Mexico. *Applied Sciences, 8*(3), 446. https://doi.org/10.3390/app8030446

Sáiz-Manzanares, M. C., Marticorena-Sánchez, R., & Ochoa-Orihuel, J. (2021). Using advanced learning technologies with university students: An analysis with machine learning techniques. *Electronics, 10*(21), 2620. https://doi.org/10.3390/electronics10212620

Shaarani, A. S., & Bakar, N. (2021). A new flipped learning engagement model to teach programming course. *International Journal of Advanced Computer Science and Applications*, *12*(9), 57–65. A New Flipped Learning Engagement Model to Teach Programming Course Shabnam-Ara S.J., Ramachandriah, T. & Haladappa, M. (2025). Predictive model to analyse real and synthetic data for learners' performance prediction using regression techniques, *Online Learning, 29*(1), 108–129. https://doi.org/10.24059/olj.v29i1.4390

Shen, Y. (2024). Examining the efficacies of instructor-designed instructional videos in flipped classrooms on student engagement and learning outcomes: An empirical study. *Journal of Computer Assisted Learning*, *40*(4), 1791–1805. https://doi.org/10.1111/jcal.12987

Shutaywi, M., & Kachouie, N. N. (2021). Silhouette analysis for performance evaluation in machine learning with applications to clustering. *Entropy*, *23*(6), 759. https://doi.org/10.3390/e23060759

Smallhorn, M. (2017). The flipped classroom: A learning model to increase student engagement not academic achievement. *Student Success, 8*(2), 43–53. https://search.informit.org/doi/10.3316/informit.593366988343831

Strobl, C., Boulesteix, A. L., Zeileis, A., & Hothorn, T. (2007). Bias in random forest variable importance measures: Illustrations, sources and a solution. *BMC Bioinformatics, 8*, 25. https://doi.org/10.1186/1471-2105-8-25

Talan, T., & Gülseçen, S. (2019). The effect of a flipped classroom on students' achievements, academic engagement and satisfaction levels. *Turkish Online Journal of Distance Education*, *20*(4), 31–60. https://doi.org/10.17718/tojde.640503

Tan, X., She, J., Chen, S., Ohno, S., & Kameda, H. (2021, July). Analysis of student learning behavior based on Moodle log data. In *2021 14th International Conference on Human System Interaction (HSI)* (pp. 1–4). IEEE. https://doi.org/10.1109/HSI52170.2021.9538680

Taşpolat, A., Özdamli, F., & Soykan, E. (2021). Programming language training with the flipped classroom model. *Sage Open, 11*(2). https://doi.org/10.1177/21582440211021403

Topalli, D., & Cagiltay, N. E. (2018). Improving programming skills in engineering education through problem-based game projects with Scratch. *Computers & Education*, *120*, 64–74. https://doi.org/10.1016/j.compedu.2018.01.011

Tran, H., Vu-Van, T., Le, T. V., Pham, H. A., & Huynh-Tuong, N. (2024). Leveraging data analytics to investigate the effectiveness of flipped classroom models: A case study of practical programming teaching. *Electronic Journal of e-Learning*, *22*(9), 144–162. https://doi.org/10.34190/ejel.22.9.3597

Turnbull, D., Chugh, R., & Luck, J. (2022). An overview of the common elements of learning management system policies in higher education institutions. *TechTrends*, *66*(5), 855–867. https://doi.org/10.1007/s11528-022-00752-7

Veerasamy, A. K., D'Souza, D., Apiola, M.-V., Laakso, M.-J., & Salakoski, T. (2020). Using early assessment performance as early warning signs to identify at-risk students in programming courses. In *2020 IEEE Frontiers in Education Conference (FIE)* (pp. 1–9). IEEE. https://doi.org/10.1109/FIE44824.2020.9274277

Villarrasa-Sapiña, I., García-Massó, X., Liébana, E., & Monfort Torres, G. (2024). Academic achievement prediction in secondary education by decision tree analysis. *Educacion XX1*, *27*(1). https://doi.org/10.5944/educxx1.33351

Wang, F. H. (2017). An exploration of online behaviour engagement and achievement in flipped classroom supported by learning management system. *Computers & Education*, *114*, 79–91. https://doi.org/10.1016/j.compedu.2017.06.012

Wang, Y., Wu, J., Chen, F., & Li, J. (2024). Analyzing teaching effects of blended learning with LMS: An empirical investigation. *IEEE Access, 12*, 42343–56. https://doi.org/10.1109/ACCESS.2024.3352169

Wiebe, E. N., Lamb, A., Hardy, M., & Sharek, D. (2014). Measuring engagement in video game-based environments: Investigation of the user engagement scale. *Computers in Human Behavior*, *32*, 123–132. https://doi.org/10.1016/j.chb.2013.12.001

Wladis, C., Hachey, A. C., Manly, C. A., & Conway, K. M. (2025). Competing hypotheses about online versus face-to-face course outcomes: Analysis leveraging the unique circumstances of the COVID-19 pandemic. *Online Learning Journal, 29*(3), 176–210. https://doi.org/10.24059/olj.v29i3.5018

Xie, J., Adjei, M., & Correia, A.P. (2024). The impact of different instructor participation approaches in asynchronous online discussions on student performance. *Online Learning, 28*(4), (34–56). https://doi.org/10.24059/olj.v28i4.4573

Yoo, J. E., Rho, M., & Lee, Y. (2022). Online students' learning behaviors and academic success: An analysis of LMS log data from flipped classrooms via regularization. *IEEE Access, 10*, 10740–10753. https://doi.org/10.1109/ACCESS.2022.3144625

Zhang, L., Chen, T., Zong, Y., & Zhang, L. (2023, October). Research to practice of blended learning in computer programming course. In *2023 IEEE Frontiers in Education Conference (FIE)* (pp. 1–5). IEEE. https://doi.org/10.1109/FIE58773.2023.10342940

Ziegenfuss, D. H., & Furse, C. M. (2021). Flipping the feedback: Formative assessment in a flipped freshman circuits class. *Practical Assessment, Research & Evaluation*, *26*, 8. https://doi.org/10.7275/007t-dj06

Zilinskiene, I. (2022). Exploring learning analytics for the course design improvement: The results of a pilot experiment. *Baltic Journal of Modern Computing, 10*(1), 36–54. https://doi.org/10.22364/bjmc.2022.10.1.03