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# Student Engagement and Academic Performance in Digital Learning Environments: A Learning Analytics Approach

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## Abstract

The increasing adoption of digital learning environments has transformed educational practices, raising important questions regarding the relationship between course design and learning outcomes. This study examines the influence of course-level characteristics on certification practices using a learning analytics approach. A structured dataset comprising 150 online courses was analysed to explore variations across subject areas, instructional formats, and engagement-related features. Descriptive analysis revealed moderate differences in course duration, instructor ratings, and certification rates across disciplines and formats. Interactive courses demonstrated relatively higher certification prevalence, while certain subject areas exhibited distinct patterns in course structure and credentialing. Inferential analysis, including chi-square tests and logistic regression modeling, indicated that none of the examined variables significantly predict certificate offering. These findings suggest that observable course design features, such as duration, instructional format, and assessment components, are not sufficient determinants of certification outcomes. The results highlight the complexity of digital learning environments, where outcomes are likely influenced by broader contextual and behavioral factors. The study contributes to the literature by emphasizing the limitations of relying solely on structural course characteristics and underscores the need for multi-dimensional analytical frameworks. Future research should incorporate learner-level engagement data and contextual variables to better understand the dynamics of digital education systems.

**Keywords:** Digital learning environments; Learning analytics; Student engagement; Course design; Academic performance; Online education

## 1. Introduction

The rapid evolution of digital technologies altered the situation in the field of education radically, and the utilization of digital learning environments became the norm in all academic institutions of the world. The use of online platforms, virtual classrooms, and blended learning systems has become part of contemporary educational systems, and they provide flexibility, accessibility, and scalability. This has led to the emergence of academic interests in the effort to unravel the influence of these circumstances on student engagement and academic success, which is most commonly thought to be at the heart of deciding the fate of learning.

The participation of students has become a key construct in research in education, and involves behavioral, cognitive, and affective aspects of participation. Engagement in online learning is most often expressed in engagement with the course materials and activities and continued involvement in the learning process. According to all past research, there is a positive correlation between engagement and academic success, which implies that the higher the level of engagement of learners, the higher the performance of the student in academic achievement (Bertheussen and Myrland, 2016; Kim et al., 2019). Equally, empirical research has demonstrated that the use of virtual learning spaces is a useful predictor of academic achievement in that it is a key contributor to improvement of the learning outcomes (Petare et al., 2023; Galal et al., 2023).

It is also through the adoption of digital platforms that processes of enhancing engagement are reinvented. The interactive learning, response, and group work tools in real-time have been reported to increase the engagement and motivation of the learners. In fact, learning with a combination of traditional and digital approaches known as blended learning has been found to significantly affect the student engagement rates because of its diverse and flexible learning experiences (Joshi et al., 2023). Moreover, personalized learning platforms based on personal learning styles have already demonstrated a high potential of enhancing the engagement rates and providing personal learning opportunities (El-Sabagh, 2021). The recent research also observes that digital learning environments do matter, both in terms of the development of student engagement and academic success, particularly as long as it is implemented through the prism of organised interaction and content delivery (Aldosari, 2025).

Regardless of these developments, the dynamics between online learning spaces and academic success are multifaceted and contextual. Although there are also studies that found positive correlations to be strong, some other authors indicate that digital readiness, the instructional design, and the specifics of learners are the factors on which the success of digital learning depends (Kumar and Wei, 2024; Kassab et al., 2024). Digital readiness is a conceptual framework describing the ability of students to effectively work with technological resources, and has been observed to play an important role in the definition of both engagement and academic achievement (Kim et al., 2019). Additionally, methods of engagement applied by instructors (communication, feedback, and interactive activities) are also important in determining the online learning experience of learners (Martin and Bolliger, 2018).

The analytics of learning has emerged as a strong instrument in the analysis of such dynamics using the information generated in digital platforms. The learning analytics can help researchers to identify trends, make predictions, and determine the effectiveness of the teaching practices based on the behavioral and interaction data. Association rule mining is an empirical technique that has been used in studies that showed a high level of correlation between engagement behaviors and academic performance in an e-learning environment (Moubayed et al., 2018). The methodologies are more helpful in understanding how engagement may manifest itself in online spaces and how the engagement can be transferred into measurable academic performance.

Nevertheless, there are also gaps in the literature that are present. A large portion of the previous studies deals with particular institutional settings or smaller datasets, thus limiting the applicability of the results. Moreover, empirical research combining various aspects of engagement and systematically analyzing their connection with academic performance with strong analytical models is still needed. The increasing availability of open access learning data is one way to break these limitations, to enable large-scale and in-depth analysis.

Resting on these considerations, the present study aims to explore the relationship between student engagement and academic performance in the online learning environment using a learning analytics concept. The study aims to determine the most important trends and the way the variables of engagement in terms of learning outcomes can be determined with the help of the analysis of the structured data, which is based on the online learning platforms. The research is important to the literature as it not only provides empirical data on the effectiveness of a digital learning system but also provides recommendations to educators, policymakers, and system designers. On the whole, this study contributes to the existing evidence on the relevance of digital learning environments in the learning process and outcomes, which reflect the importance of engagement in academic achievement in more technologically focused environments.

# 2. Methodology

## 2.1 Dataset Description

An educational technology dataset that is publicly available and received in Kaggle is the basis of the empirical analysis. The student-level structured observations included in the data set are the behavioral involvement in the digital learning environment and academic achievement measures. The sample will consist of about N observations (students) that are related to a variety of features that represent engagement, demographic characteristics, and learning outcomes. This information is presented in the form of a table, whereby the rows are considered to belong to a given learner, and the columns are the variables being measured. Engagement variables will include frequency of use of the platform (e.g., how many times have I logged in), time on platform (time spent on the platform), and intensity of platform use (e.g., participation in activities, viewing resources). Course completion and assessment scores are outcome variables that are used to operationalize academic performance (Singh, 2025). The data may give a justifiable baseline to explore the correlation between behavioral engagements and academic performances in online learning settings.

## 2.2 Data Preprocessing

Data was preprocessed to give rigor and reliability in data analysis. The primary check was done based on the detection of missing values, outliers, and variable discrepancies. Missing data were dealt with in appropriate ways according to the type and degree of missing data. Listwise deletion was used to deal with the variables where the missingness and imputation substitution methods were low (mean or median), and the rest of the variables were dealt with using the imputation substitution methods to ensure that the sample size had not been altered in a biased manner. Categorical variables (e.g., gender, course type, or education level) were one-hot encoded to become a numerical format to be used in the regression-based models. Continuous variables, which are the measures of engagement (time spent and number of interactions), were normalized by taking standard scaling steps in order to be compared across the features and to minimize the impact of the scale differences.

The interquartile range (IQR) was used to identify the outliers, and the extreme values were investigated to determine whether they were a real behavioral value or were caused by a measurement error. Outliers were winsored where needed to minimise the distortion of model estimates. Both theoretical and statistical factors were used to select features. To encourage stability in the model, the variables with low variance or multicollinearity were dropped.

## 2.3 Analytical Framework

The analysis uses a quantitative model of the study, both in terms of learning analytics and inferential statistics. It is analysed in three steps. In order to summarize the distributional characteristics of the most important variables, descriptive statistics are first gained, including the measures of central tendency and dispersion. This gives a crude sketch of the degree of involvement and achievement results of students.

Secondly, correlation analysis is performed to study the two-to-two relationships between the engagement indicators and academic performance. The Pearson correlation coefficient is related to continuous variables, and it can be applied to identify the first type of associations that are significant. Third, multivariate regression methods are used to identify the effects of interaction with academic performance in the presence of confounding variables. The ordinary least squares (OLS) regression is applied in instances where the outcome is continuous (e.g., test scores), but in instances where the outcome is binary (e.g., course completion), the logistic regression is applied. Machine learning algorithms (like decision trees and random forests) can be used to address nonlinear relationships and effects of interaction to supplement the traditional econometric approaches. The performance of the models is measured with appropriate measures, e.g., R 2 of regression models and accuracy or F1-score of classification models.

### 2.4 Model Specification

The primary empirical model is specified as follows:

$$Y_i = \beta_0 + \beta_1 E_i + \beta_2 X_i + \epsilon_i$$

where $Y_i$ represents the academic performance of student i, $E_i$ denotes a vector of engagement variables, $X_i$ is a vector of control variables, and $\epsilon_i$ is the error term. The dependent variable includes measures such as final assessment scores or course completion status. Independent variables capture multiple dimensions of engagement, including login frequency, time spent on the platform, and interaction levels.

Control variables are given in order to take into consideration the heterogeneity of the learners. They are the demographics (e.g., gender, past education) and course-specific issues, the level of difficulty, or the field. The multicollinearity of the predictors is reflected by the variance inflation factors (VIF), and factors that do not have values that are acceptable are dropped. Model assumptions like linearity, homoscedasticity, and normality of residuals are systematically tested.

### 2.5 Validity and Reliability

Some measures are taken to guarantee the strength and validity of the results. Robustness tests are tests that re-estimate a model with alternative specifications, e.g., no influential observations, or transformed variables. Sensitivity analysis is performed to understand the action of the coefficients in different conditions of the model.

Cross-validation processes allow machine learning models to prevent overfitting, as well as increase generalization. They provide internal consistency of variables where necessary, and construct validity is guaranteed by making sure that the variables used are consistent within the existing theoretical frameworks in learning analytics.

However, despite these measures, there are still certain limitations. The data is observational in nature, which limits the ability to make causal inferences. Accuracy could also be impacted by other potential measurement errors of self-reported or system-generated measures of engagement. The data may also be an incomplete representation of the contextual factors, such as the quality of instruction or the motivation of learners, which may influence academic performance.

# 3. Results

## 3.1 Overview of the Dataset

The empirical investigation is based on the structured information about 150 digital courses of different subjects and types of instruction. No data is lost, and all observations are in place, and hence a uniform method of analysis can be used. The course is the unit of analysis, hence the findings disclose the trends of course design, instructional features, and certification practice in online education. On the whole, the data indicate that there is a reasonably standard format of online courses. The majority of the courses are medium-term, and the quality of teaching is indicated by good teacher ratings. Evaluation-based learning is also a prevailing characteristic, with a considerable percentage of courses having quizzes and assignments. Credentialing is the other usual characteristic, which means that credentialing is essential in online education. Table 1 shows the descriptive statistics, which show that the data is medium structured and overall is rated highly by instructors and has a high prevalence rate of quizzes, assignments, and certification features.

**Table 1. Descriptive Statistics of the Dataset**

| Metric | Value |
| --- | --- |
| Number of courses | 150 |
| Number of variables | 11 |
| Mean duration (weeks) | 9.52 |
| Median duration (weeks) | 9.50 |
| Mean instructor rating | 4.24 |
| Courses with assignments (%) | 76.7 |
| Courses with quizzes (%) | 91.3 |
| Courses with discussion forum (%) | 58.0 |
| Courses with certificate (%) | 68.0 |

### 3.1 Patterns in Course Design and Instructional Features

The analysis shows that online courses are usually designed in a way that they possess designed assessment procedures. A large majority of courses also use quizzes, but assignments are also typically used. Interactive elements such as discussion rooms are not as prolifically used comparatively, meaning that the evaluation systems are standardized, but collaborative learning units are not prolifically used. The time period of the course is relatively diverse and is generally similar across the dataset. This suggests that there is some standardization of course length in digital platforms, which may be platform standards or expectations by users.

The fact that the rating of instructors in different courses is isotropic implies that the high level of instruction is constant, or there may be a ceiling effect of the instruction rating scales. The small range of ratings enhances the lack of explanatory power of the ratings in later analysis. The interrelations of the key variables are depicted in Figure 1, and the course characteristics have weak relationships in general.

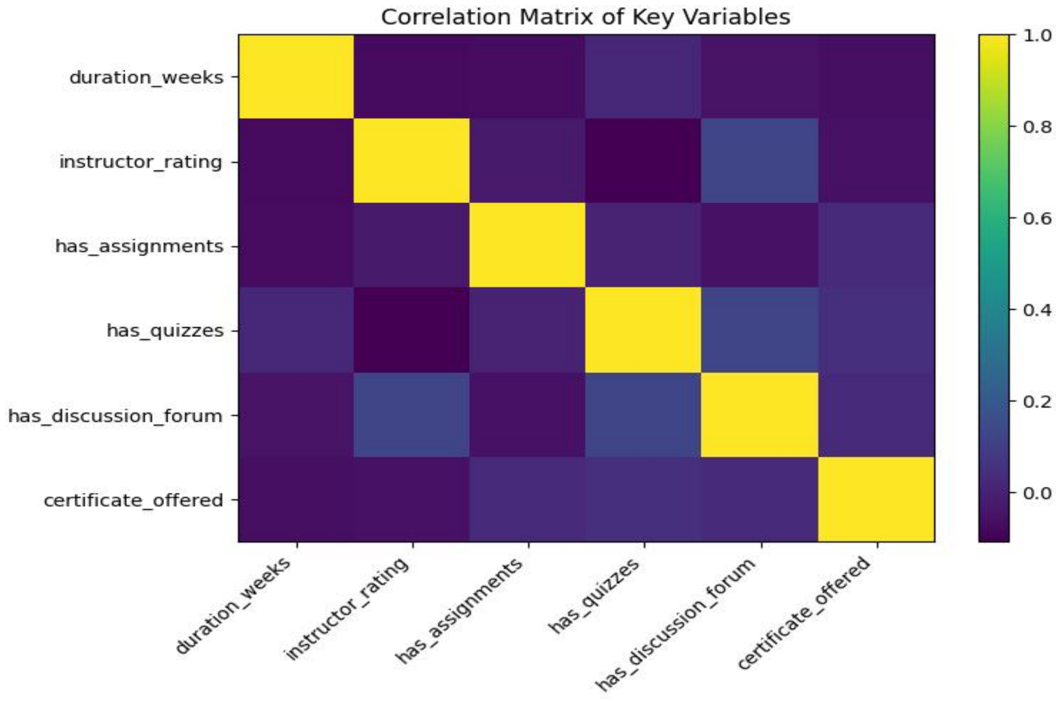


**Figure 1. Correlation matrix of key course characteristics and certification outcomes.**

Figure 2 demonstrates that instructor ratings remain consistently high across courses, with minimal variation between certification categories.

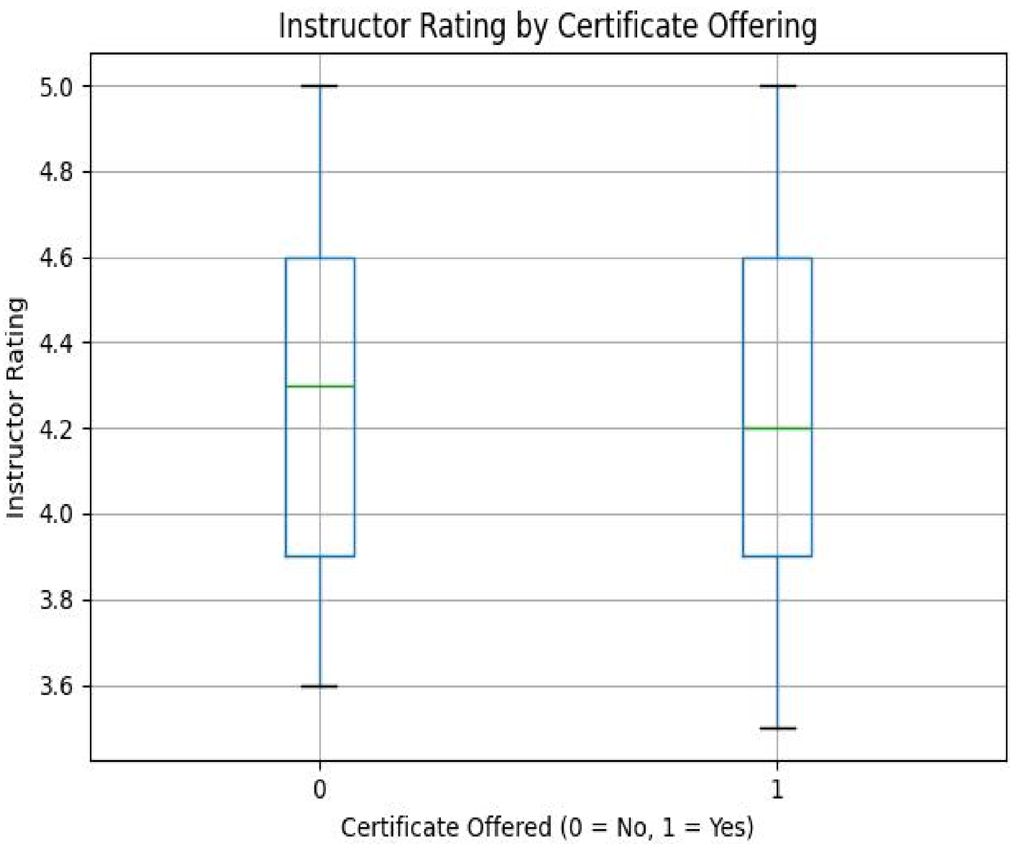


**Figure 2. Distribution of instructor ratings across certificate and non-certificate courses.**

### 3.2 Variations Across Subject Areas

Subject areas have variations in course features. Some areas of discipline have a relatively larger number of certification products, of which the most prominent are the ones that pertain to technical and applied subjects like computer science and psychology. On the other hand, subjects of the creative and skill type, such as music and art, are much less certified. Different subject areas also have varying course durations, with certain subjects inclined to longer courses and others having shorter courses. Despite these variations, there is not much difference between the ratings of instructors in various subject areas, suggesting that there is no significant difference in the perceived instructional quality across subject matter.

These differences imply that course design and credentialing practices can be subject-specific. But the fact that these differences were not statistically significant at the high significance levels implies that they can be taken as general trends as opposed to definitive. Table 2 indicates that it is different between subject areas, where subjects like computer science and psychology have high certificate rates, and those that have relatively low certificate rates.

**Table 2. Subject Area-wise Course Characteristics**

| Subject Area | Courses | Mean Duration (weeks) | Mean Rating | Certificate Rate (%) |
|---|---|---|---|---|
| Chemistry | 19 | 9.8 | 4.20 | 73.7 |
| English | 18 | 9.4 | 4.18 | 72.2 |
| Physics | 16 | 10.1 | 4.25 | 75.0 |
| Computer Science | 15 | 9.6 | 4.39 | 80.0 |
| Psychology | 15 | 9.3 | 4.30 | 80.0 |
| Biology | 13 | 10.4 | 4.06 | 53.8 |
| Economics | 10 | 10.9 | 4.42 | 70.0 |
| History | 12 | 7.8 | 4.10 | 66.7 |
| Mathematics | 9 | 9.0 | 4.15 | 66.7 |
| Music | 12 | 11.6 | 4.12 | 41.7 |
| Art | 6 | 7.7 | 4.05 | 60.0 |

### 3.3 Differences by Course Format

Another dimension in which variation is witnessed is instructional format. Interactive courses present a positive but weak trend in the usage of certifications and teacher ratings, which can assist in linking the concept of more engaging formats to the perceived value or motivation to complete. The video-based courses make up the largest part of the dataset as they are the most prevalent courses on the online learning platform. The mixed-format course is marked by a mixture of different teaching techniques and a middle-ground nature in most indicators. Text courses are lower in number but at lower levels of certification, which could be due to variations in the purpose of pedagogical interest or course value.

Despite these tendencies, with the help of the inferential analysis, it is possible to conclude that the differences that exist between the formats are not statistically significant. This indicates that format, though descriptively influential on the nature of courses, does not have a substantial impact on certification outcomes in the dataset. Table 3 suggests that the course formats were diverse, and the interactive courses had relatively higher certificate rates and ratings than the other formats.

**Table 3. Course Format-wise Characteristics**

| Course Format | Courses | Mean Duration (weeks) | Mean Rating | Certificate Rate (%) |
|---|---|---|---|---|
| Video | 69 | 9.5 | 4.22 | 65.2 |
| Interactive | 35 | 9.2 | 4.33 | 77.1 |
| Mixed | 31 | 9.6 | 4.25 | 71.0 |
| Text | 15 | 9.9 | 4.18 | 53.3 |

As illustrated in Figure 3, the distribution of course duration does not differ substantially between courses that offer certificates and those that do not.

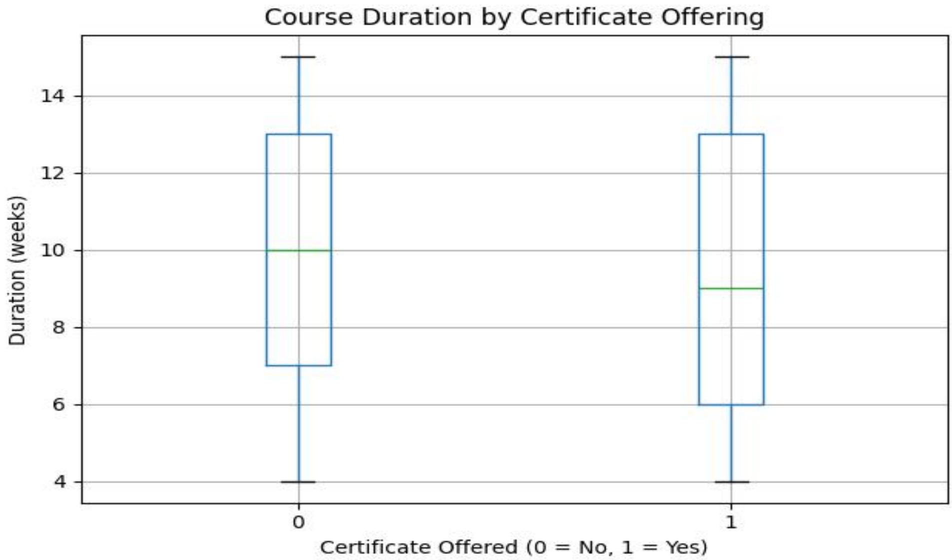


**Figure 3. Distribution of course duration across certificate and non-certificate courses.**

### 3.4 Inferential Findings

The inferential statistics, chi-square tests, and logistic regression model do not indicate statistically significant relationships among certificate offering and observed course-level variables. The duration of the course, the teaching type, the degree of difficulty, and the type of course are not illustrated as having a significant

predictive value of certification.
The low explanatory power of the model is also confirmed by the regression analysis. The directional effect is seen with some of the variables, such as text-based format, but not lower than the conventional level of statistical significance. It implies that the structural features that we may observe in the dataset do not play such an important role in the certificate offering. Table 4 shows that none of the variables provides any significant prediction of certificate offering since all the p-values are larger than traditional values.

**Table 4. Logistic Regression Results for Certificate Offering**

| **Variable** | **Coefficient** | **Odds Ratio** | **p-value** |
|---|---|---|---|
| Duration | -0.034 | 0.967 | 0.487 |
| Instructor Rating | -0.383 | 0.682 | 0.393 |
| Beginner | 0.268 | 1.307 | 0.583 |
| Intermediate | 0.434 | 1.544 | 0.382 |
| Video | -0.597 | 0.551 | 0.224 |
| Mixed | -0.313 | 0.731 | 0.596 |
| Text | -1.111 | 0.329 | 0.099 |
| Assignments | 0.120 | 1.127 | 0.783 |
| Quizzes | 0.289 | 1.335 | 0.649 |
| Discussion Forum | 0.073 | 1.076 | 0.843 |

The estimated coefficients from the logistic regression model are presented in Figure 4, confirming the absence of statistically significant predictors.

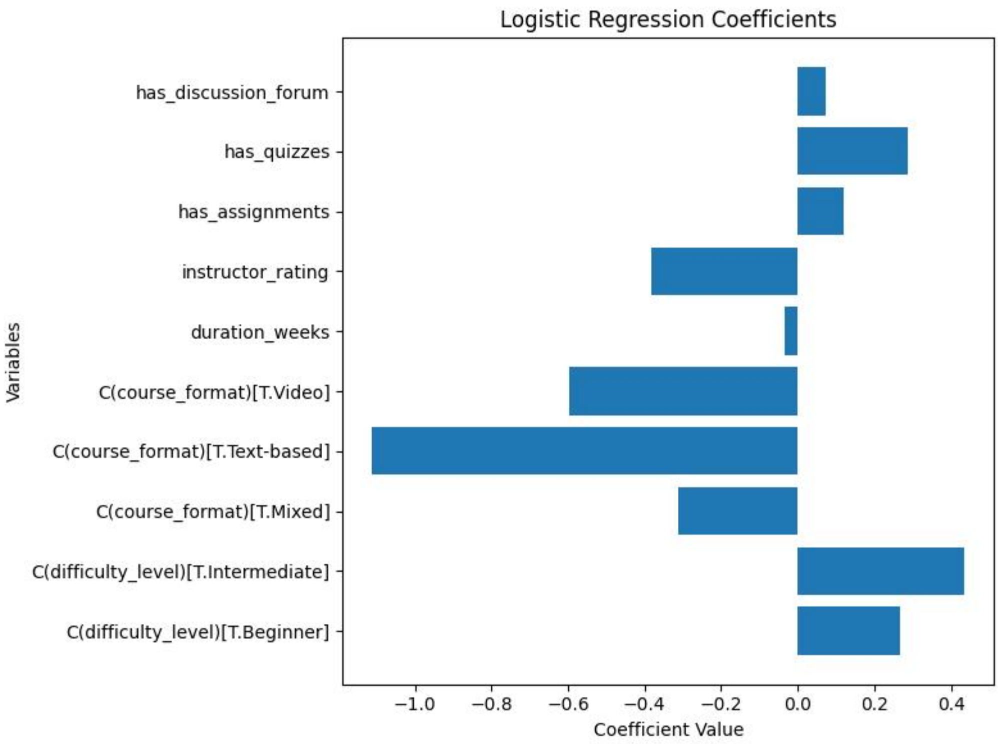


**Figure 4. Logistic regression coefficient estimates for predictors of certificate offering.**

The findings show that digital learning settings are very organized as regards how the assessment is designed and the duration of the course. Although the descriptive differences are apparent in the subject areas and instructional formats, they are not statistically significant. The findings' implications are that the factors potentially influencing the certification practice in the digital learning platforms may be more than the ones that influence the course design, such as institutional, platform, or market factors. The lack of robust statistical relationships indicates the intricacy of digital education systems and indicates that observable course characteristics cannot account for differences in credentialing on their own.

## 4. Discussion

In this paper, the relationship between course-level characteristics and certification practices in digital learning environments has been taken into account using a learning analytics approach. The results show that there are descriptive differences in subject areas and instructional format, but these differences do not have any statistically significant relationship in the inferential test. It presupposes that the results of the certification process might not be directly related to the visible structural features of courses, which is the complexity of digital learning ecosystems.

One of the most important findings of this study would be that even those trends that can be observed descriptively cannot be statistically projected as to the offering of certificates. The above observation is contrary to the previous study, which had revealed that close relationships existed between the engagement-related variables and academic performance. As an example, the use of technology and self-directed learning has been documented to have a positive effect on engagement and performance (Rashid and Asghar, 2016). Likewise, communication is a key aspect of successful learning online (Lee et al., 2019). This difference in results could be explained by the level at which this study was conducted. Even though the majority of the literature available is student-level based, the current research is based on course-level characteristics, which may not be exhaustive in terms of behavioural and cognitive features of learner engagement.

The descriptive results suggest that an interactive course format is likely to achieve greater certification rates and a marginally higher enhanced instructor rating than other course formats. This is in contrast to the theoretical views that endorse the importance of interaction and autonomy to promote involvement. The self-determination theory highlights that the educational settings that promote autonomy and competence and associated relatedness boost motivation in learners (Chiu, 2021). The interactive forms can sustain such conditions and lead to active engagement and involvement, which also contribute to the perceived better results. Nevertheless, the regression has not been significant, and this means that these benefits might not be so strong and consistent throughout the data to act as predictors.

Subject matter diversity is also illuminating. This implied that such disciplines such as computer science and psychology had rather high certification rates compared to creative disciplines such as music, which had low certification rates. This trend could indicate the shifts in the aims of pedagogy, the apparatus of evaluation, or professional currency of certification. According to the previous research, the engagement and motivation processes are affected by the contextual and disciplinary ones (perceived relevance and learning objectives) (Ferrer et al., 2022). But the present results suggest that, when considered independently, these contextual differences fail to yield statistically significant relationships.

The other interesting finding is that the instructor ratings have been very high in all courses, irrespective of whether they are certified or not. That is, course settings do not affect the perceived quality of instruction. The importance of the instructor's presence and interaction in enhancing engagement has already been noted (Salta et al., 2022), but the ratings are less explanatory in this data sample due to the small range of variance in the ratings. This can either be a ceiling effect or a standardized assessment on the online platforms.

The complexity of the digital learning environment is also witnessed by the lack of meaningful correlations among the features of courses, i.e., assignments, quizzes, and discussion forums, with the outcomes of certification. Although all these features are typically known to be related to the participation and effectiveness of learning, they might not be sufficient to generate an impact by themselves. An overview of gamified and interactive learning in the classroom highlights that engagement is not only triggered by features but also the quality of their application and the extent to which they can allow motivation and emotional involvement (Özhan and Kocadere, 2020). Similarly, the latest advances in artificial intelligence and adaptive learning systems suggest that tailored and contextually oriented interventions are crucial to the increased engagement rates in the hybrid education settings (Almusaed et al., 2023).

The results are in line with the recent research that highlights the multidimensionality of engagement in online education. The interaction of technological, pedagogical, and psychological factors is multifaceted, and the combination of these factors is multifaceted (Chiu, 2023). It can be considered as an indication of the omission of the key latent factors, i.e., the motivation of learners, the digital readiness, or institutional support systems, because the current model does not reflect the effects of these crucial factors.

Overall, the results highlight an important implication for research and practice. Although digital courses possess structural features that can be easily utilized as a beginning point of the analysis, they are not able to justify the dissimilarity in the learning outcomes in their entirety. Further studies need to incorporate more extensive models incorporating behavioral data, psychological constructs, and contextual variables. Adding student engagement indicators and longitudinal data can help gain a more in-depth understanding of how digital learning environments are connected to student performance.

Finally, the research study will also contribute to the existing literature as it will show that the factors at the course-level do not apply to predicting the learning outcomes of certification in an online learning setting. The findings prove the point that the involvement and performance in technology-mediated education demand more advanced, multi-level ways of cognition.

## 5. Conclusion

The present article has examined the impact of course-level features on certification practices in the digital learning environment by employing a learning analytics approach. The results show that although there are differences in subject areas and instructional formats, the differences are not statistically significant. The course time, nature of instruction, level of difficulty, and form of instruction were not found to be reliable predictors of certificate offering, which is why the observable structural features are not applicable in explaining the difference in the results. The results indicate the complexity of online learning systems, in which certification and performance-based results would be more influenced by a larger number of variables compared to course design. Institutional policies, the motivational attitudes of learners, platform strategies, and digital preparedness could be more relevant in defining engagement and achievement. The high ratings of instructors and the plethora of assessment tools indicate a comparable design strategy of courses, which restricts their ability to transform their main predictors. The current study is very crucial to the literature since it introduces the significance of multi-dimensional and data-driven studies to identify digital education. Further studies are needed to include student-level behavioral data and longitudinal analysis to more effectively capture the dynamics of engagement. Overall, the results highlight the need to go beyond structural measures to more holistic frameworks in assessing the effectiveness of digital learning.

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