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# BEHAVIORAL ENGAGEMENT AND ACADEMIC SUCCESS IN ONLINE EDUCATION: AN ANALYSIS OF STUDENT INTERACTION PATTERNS

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***Abstract***
*This study examines the relationship between behavioral engagement and academic success in online learning environments by analyzing student interaction patterns derived from a structured dataset. The quantitative research design was adopted with the use of a secondary dataset, retrieved on Kaggle (xAPI-Edu Data), which contains 480 records of students. Participation, resource use, announcement interaction, and discussion activity were some of the indicators that were used to measure behavioral engagement. Python was used to analyze the data with descriptive statistics, reliability analysis, Pearson correlation, ANOVA, and multiple linear regression. The findings show that there is a positive and strong relationship between academic performance and behavioral engagement. The most important predictors of academic success identified were resource utilization and active involvement, with limited contribution of passive engagement. A major discrepancy in engagement was noted among performance groups. The results emphasize the value of creating interactive and student-focused online learning platforms that facilitate active learning. The research adds to the existing body of literature by employing real-world LMS data and Python-based analysis to present a data-driven insight into the dynamics of engagement in online education.*

***Keywords:*** *Behavioral Engagement, Online Learning, Academic Performance, Learning Analytics, Student Interaction, Educational Technology*

## 1. Introduction

The fast growth of online and technology-based learning environments has greatly changed the way education is being conducted worldwide. As Learning Management Systems (LMS) and online platforms are gradually replacing traditional learning methods, educational research has begun to focus on how students engage with each other in these spaces and how this interaction affects learning outcomes. One of the most important factors that has been raised as a decisive factor of student achievement in online learning is behavioral engagement, which refers to the visible activities and involvement of students in the learning process (Fredricks et al., 2004). Unlike in the traditional classroom environment, the online learning space is highly dependent on the digital traces of student activity, and it is thus possible to analyze the patterns of the interaction systematically and in connection to the performance (Henrie et al., 2015).

Online education is usually operationalized by using measures of student involvement in the process (i.e., the number of discussions they participate in, the number of times they visit learning materials, how responsive they are to announcements, and the degree to which they are involved in the instructional process) (Kahu, 2013). Such behavioral cues are useful in understanding how students maneuver and use digital learning resources. Past studies indicate that the students who are interested in the material of courses and engage in interactive activities are more likely to have better academic results (Kuh, 2009). Moreover, engagement has been associated with enhanced retention, motivation, and overall learning effectiveness, and therefore it ought to be considered as a focal construct in the study of education (Trowler, 2010; Zhu et al., 2020).

Although there is an increasing amount of literature on the topic of student engagement, the existing studies have focused on the traditional or blended learning contexts, and little focus has been directed towards the purely online setting (Bond et al., 2020; Martin & Bolliger, 2018). Also, previously, researchers tended to use self-reported indicators of engagement, which could be biased and were not necessarily the true picture of student behavior (Henrie et al., 2015). Contrastingly, the accessibility of massive datasets of educational activities created by LMS systems provides fresh possibilities to analyze engagement based on the objective behavioral metrics. These datasets allow the researchers to reach the patterns of interaction in real-time and allow a more detailed depiction of the impact of engagement on academic performance (Gašević et al., 2015; Joksimović et al., 2015).

Nevertheless, a considerable research gap is still present in terms of the combination of various behavioral indicators of engagement into a complex analytical model that would study their overall impact on academic achievement. Although the effect of individual variables, including the use of resources or engagement, has been examined independently, limited studies have investigated how the various dimensions of engagement interrelate to impact learning in virtual classrooms (Dixson, 2015). Additionally, empirical studies that use secondary data on platforms like Kaggle, which have full, real-world learning data, are scarce and can be analyzed with advanced statistical methods. The inadequacy of the body of research using such datasets limits the generalization and the applicability of results in modern digital learning settings.

The second gap is related to methodological approaches to the analysis of engagement data. Most of the current researchers are yet to maximize on the use of computational tools and statistical model methods, which can further illuminate the predictive relationships between engagement behaviors and academic success (Siemens & Baker, 2012). This analysis can be done through the use of analytical tools that are based on programming, including Python, which allow stronger data processing, visualization, and modeling, and increase the reliability and reproducibility of the research results. In spite of this possibility, research that combines the recent analytical methods with the data on education to generate evidence-based results is still required.

To address these gaps, the current research study will focus on the research question of whether behavioral engagement is related to academic success in online learning by classifying patterns of student interaction based on structured data. The paper is concerned with the crucial engagement metrics, such as participation, resource usage, engagement in communication, and discussion activity, to evaluate their impact on academic performance. Using a secondary dataset that is available on Kaggle and implementing a statistical analysis using Python, the study aims to offer a wholesome and evidence-based insight into engagement mechanics in online learning settings.

The main aim of the study is to explore the significance of various aspects of behavioral engagement in the academic achievement of students in online learning. In particular, the research will examine the trends in student interaction in an online learning environment, assess the level and nature of the relationships among the variables of engagement and the outcomes of performance, and determine the strongest predictors of academic success. In such a way, the study makes a contribution to the literature body as it discusses the shortcomings of the previous research and provides empirical data, which is based on real educational information.

This study is informative to educators, instructional designers, and policy makers by closing the gap between theoretical constructs of engagement and empirical research on student behavior. Knowing the role of engagement in academic success would help to create more effective online learning strategies and interventions. Finally, the study would improve the quality of online learning by highlighting the significance of participative learning and interaction as a means of attaining positive learning outcomes.

## 2. Methodology

### 2.1 Research Design

This research is a quantitative study that will be used to determine the relationship between behavioral engagement and academic achievement in online learning settings. It is an empirical study that uses statistical analysis to determine the patterns and the association between the variables. It takes a cross-sectional design since the data are an observation at

one time and not a longitudinal follow-up. The design is suitable for studying structured data and also for examining the relationship between interaction behaviors and the academic performance outcomes of students in a digital learning environment.

**2.2 Data Source**

The study is based on a secondary dataset obtained from the Kaggle platform, specifically the widely used xAPI-Edu Data dataset (Raj B., 2025). The initial collection of this dataset was on an online learning management system called Kalboard 360, which monitors student engagement and actions in a virtual learning space. The sample comprises some 480 student records and consists of both demographic and behavioral variables along with academic variables. The behavioral data are created using the Experience API (xAPI) that captures specific data regarding the student engagement, including access to the learning materials, taking part in discussions, and interacting with the course announcements. A secondary dataset provides an opportunity to effectively analyse real-life learning data and still maintain a connection between the study and actual student behaviour in an online education platform.

**2.3 Sample and Data Characteristics**

The dataset is 480 student observations, and this is large enough to do statistical analysis. The sample will cover students across various educational levels, grades, and classrooms, making it diverse in terms of learning environments. The sample size includes both male and female students and reflects a variety of nationalities, and thus, demographic features could be variable.

The academic performance of students is divided into three groups: low (n = 127), medium (n = 211), and high (n = 142), and shows that the majority of students belong to the medium performance group. This distribution supports meaningful comparative analysis across performance groups.

The dataset has several behavioral engagement variables such as the frequency of raising a hand in the classroom (M = 46.78, SD = 30.78), number of times a student accesses learning resources (M = 54.80, SD = 33.08), the number of times a student views announcements (M = 37.92, SD = 26.61), and the These variables are different aspects of student interaction in the online learning environment.

Also, contextual variables (student absence under seven days and over seven days) and the indicator of parental involvement are added, which sheds more light on the variables that might impact academic performance. The multi-dimensional and structured format of the data allows using it easily in statistical modeling, correlation analysis, and predictive modeling with the help of Python-based analytical tools.

**2.4 Variables and Measurement**

In this study, behavioral engagement is the main independent construct that is operationalized with the help of several observable indicators based on the dataset. These variables are the number of raised hands as a measure of active learning, frequency of accessing learning materials as a measure of self-directed learning, number of announcements as a measure of course attentiveness, and involvement of discussing forums as a measure of interactive learning. All these variables are a reflection of the patterns of student interaction in the online learning environment.

The dependent variable is academic success, which is measured using the categorical variable denoted as class performance, which categorizes students into low, medium, and high performance. To enable correlation and regression modeling, this variable is numerically coded to ease the statistical analysis. Besides the main variables, some control variables, including the number of days when students were absent and parental engagement indicators, are selected to take into account the external factors impacting academic performance. The operationalization of these variables allows the overall evaluation of the effect of behavioral engagement on academic performance.

**2.5 Data Analysis Procedure**

Data analysis in this study is done by using Python, which is a popular programming language in statistical computing and data analysis. The data is initially loaded and manipulated through the Pandas library, which facilitates easy data cleaning, transformation, and manipulation. NumPy is used to do numerical calculations and array operations, and Matplotlib and Seaborn are used to do data visualization to demonstrate patterns and distributions.

Descriptive statistics are used as the starting point of the analysis to describe the most prominent features of the data, such as central tendency and dispersion measures. This is then succeeded by reliability analysis, in which Cronbach's alpha is calculated to determine the internal consistency of the behavioral engagement construct, which is a combination of various engagement indicators. Then, Pearson correlation analysis is done to determine the direction and strength of relationships between behavioral engagement variables and academic performance.

To explore further the predictive ability of engagement behaviors, multiple linear regression analysis is conducted with statistical modeling libraries, e.g., Statsmodels or Scikit-learn. This enables the determination of important predictors of academic success and offers an understanding of the relative value of each engagement variable. Python has been used to ensure the reproducibility, accuracy, and flexibility in manipulating the dataset, which makes it a suitable tool that can be used to perform in-depth analysis of the educational data.

**3. Results**

**3.1 Descriptive Statistics**

Table 1 provides the descriptive statistics of the variables in the study. The findings show moderate to high variability among all behavioral engagement indicators. The average raised hands mean score is 46.78 (SD = 30.78), indicating that there is a significant range in student engagement. In the same way, the average of visited resources (M = 54.80, SD = 33.08) and the announcements viewed (M = 37.92, SD = 26.61) reveal that there is a variation in the degree of engagement with learning resources and course communication. The variability in participation in discussions is also evident, with a mean of 43.28 (SD = 27.64).

Mean behavioral engagement score is 45.69 (SD = 23.26), which shows a moderate level of overall engagement among the students. The mean of academic performance as a coded variable (1 = Low, 2 = Medium, 3 = High) is 2.03 (SD = 0.75), which implies that the majority of the students are in the medium performance group.

**Table 1. Descriptive Statistics of Study Variables**

| Variable | Count | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| Raised Hands | 480 | 46.78 | 30.78 | 0 | 15.75 | 50 | 75 | 100 |
| Visited Resources | 480 | 54.80 | 33.08 | 0 | 20 | 65 | 84 | 99 |
| Announcements Viewed | 480 | 37.92 | 26.61 | 0 | 14 | 33 | 58 | 98 |
| Discussion Participation | 480 | 43.28 | 27.64 | 1 | 20 | 39 | 70 | 99 |
| Behavioral Engagement Score | 480 | 45.69 | 23.26 | 1 | 26 | 46 | 64.31 | 92 |
| Academic Performance (coded) | 480 | 2.03 | 0.75 | 1 | 1 | 2 | 3 | 3 |

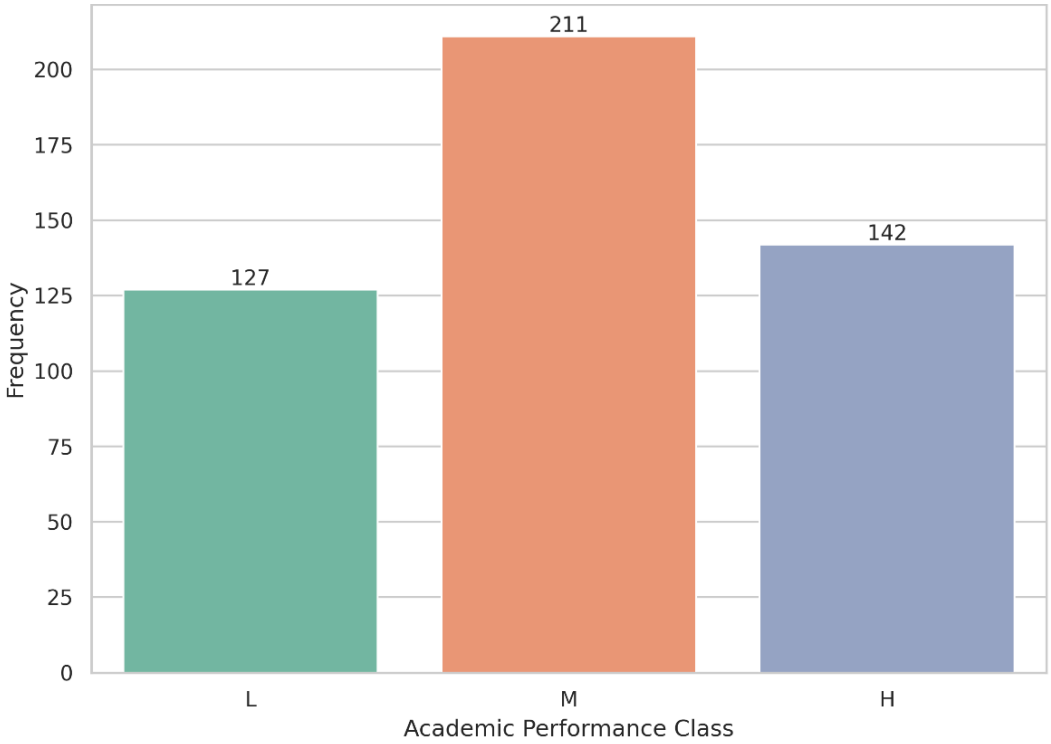


**Figure 1. Distribution of Academic Performance Levels**

Figure 1 illustrates the distribution of levels of academic performance, with most of the students having medium performance levels (n = 211), high performance levels (n = 142), and low performance levels (n = 127).

### 3.2 Reliability Analysis

Cronbach's alpha was used to measure the internal consistency of the behavioral engagement construct. The achieved alpha value of 0.792 reflects a reasonable level of reliability, which means that the chosen engagement variables (raised hands, visited resources, announcements viewed, and participation in discussions) are always used to measure the latent construct of behavioral engagement. This degree of reliability justifies the combination of these indicators into a composite engagement scale to be further analyzed.

### 3.3 Correlation Analysis

Pearson correlation analysis was used to test the relationships between the variables of behavioral engagement and academic performance. The findings given by Table 2 indicate that all engagement indicators have a positive correlation with academic achievement.

The most strongly correlated with academic performance is visited resources (r = 0.677), then raised hands (r = 0.646), and announcements viewed (r = 0.527). There is a weaker yet positive relationship in discussion participation (r = 0.308).

The composite behavioral engagement score is positively correlated with the score of academic performance (r = 0.697), which implies that the greater the level of engagement, the better the academic performance.
The correlation table is visually depicted in Figure 2, which shows the magnitude and direction of relationships between variables.

**Table 2. Pearson Correlation Matrix**

| Variable | RH | VR | AV | D | BES | Class |
|---|---|---|---|---|---|---|
| Raised Hands (RH) | 1 | 0.692 | 0.644 | 0.339 | 0.862 | 0.646 |
| Visited Resources (VR) | 0.692 | 1 | 0.595 | 0.243 | 0.826 | 0.677 |
| Announcements Viewed (AV) | 0.644 | 0.595 | 1 | 0.417 | 0.834 | 0.527 |
| Discussion (D) | 0.339 | 0.243 | 0.417 | 1 | 0.615 | 0.308 |
| Behavioral Engagement Score | 0.862 | 0.826 | 0.834 | 0.615 | 1 | 0.697 |
| Academic Performance | 0.646 | 0.677 | 0.527 | 0.308 | 0.697 | 1 |


**Figure 2. Correlation Matrix of Behavioral Engagement Variables and Academic Performance**

### 3.4 ANOVA Results

One-way ANOVA was used to test the differences in behavioral engagement between academic performance groups. The findings of Table 3 show that the difference in the engagement scores between the three performance groups is statistically significant ($F = 242.36$, $p < 0.001$). This observation implies that students who achieve high grades have much higher behavioral engagement levels than low-performing students.
Figure 3 visually illustrates this trend, with more engaged students showing scores that are significantly higher with increasing performance.

**Table 3. ANOVA Results for Behavioral Engagement Across Performance Groups**

| Source | Sum of Squares | df | F | p-value |
|---|---|---|---|---|
| Class | 130663.33 | 2 | 242.36 | 0.000 |
| Residual | 128581.28 | 477 | | |

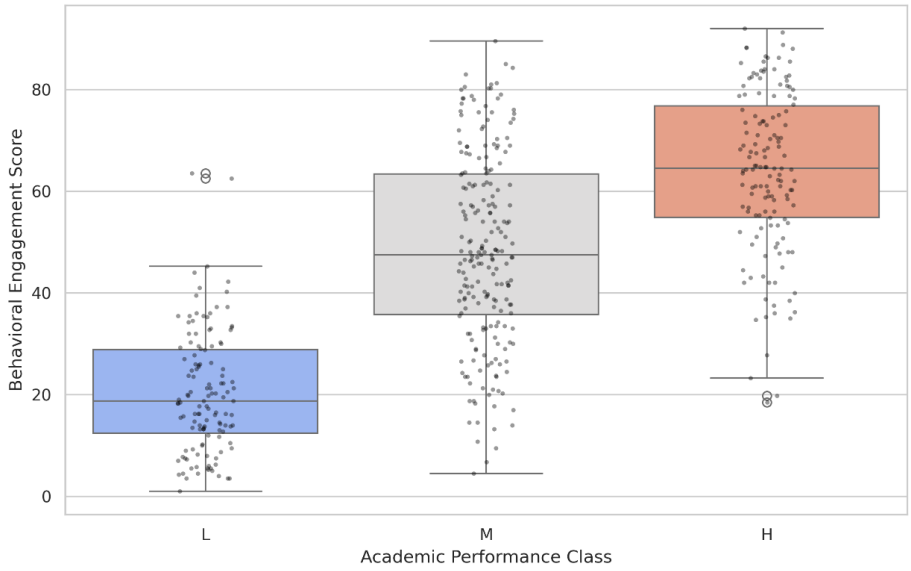


**Figure 3. Behavioral Engagement Scores Across Academic Performance Groups**

### 3.5 Regression Analysis

A multiple linear regression was used to determine the predictive power of the behavioral engagement variables on academic performance. Since academic performance is categorical, it was coded numerically (1 = Low, 2 = Medium, 3 = High) so that it can be analysed using regression analysis.

Table 4 shows that the strongest predictors of academic success include the visited resources ($\beta = 0.0096$, $p < 0.001$) and raised hands ($\beta = 0.0071$, $p < 0.001$). The positive effect of participation in discussions is also statistically significant ($\beta = 0.0023$, $p = 0.016$). Nonetheless, there is no statistically significant impact of announcements seen on academic performance ($p = 0.234$).

These results indicate that engagement behaviors, especially using learning resources and attending classroom activities, are critical in defining academic achievements in online learning environments.

**Table 4. Multiple Regression Results**

| Variable | Coefficient | Std Error | t-value | p-value |
|---|---|---|---|---|
| Constant | 1.0193 | 0.054 | 18.886 | 0.000 |
| Raised Hands | 0.0071 | 0.0012 | 6.045 | 0.000 |
| Visited Resources | 0.0096 | 0.0010 | 9.353 | 0.000 |
| Announcements Viewed | 0.0015 | 0.0013 | 1.192 | 0.234 |
| Discussion | 0.0023 | 0.0009 | 2.416 | 0.016 |

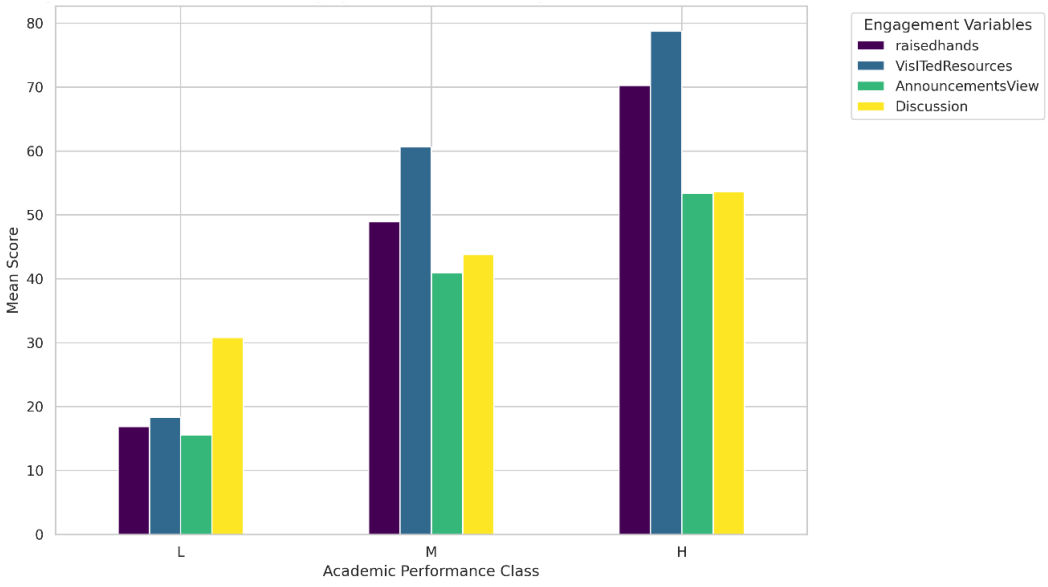


**Figure 4. Mean Behavioral Engagement Indicators by Academic Performance Level**

The variations in the levels of engagement as per the categories of performance are further depicted in Figure 4, which shows the mean behavioral engagement indicators of each performance group. The figure makes it clear that there is a steady rise in low- to high-performing student engagement, which supports the statistical results.

### 3.6 Summary of Findings

On the whole, the findings offer good empirical support for the positive correlation between behavioral engagement and academic achievement. The results of descriptive statistics, correlation analysis, ANOVA, and regression show that the more actively involved students in online learning activities, the better their academic performance is expected to be. Resource usage and active participation are the most effective engagement indicators that predict success, as the importance of interactive and participatory learning environments is revealed.

## 4. Discussion

The findings of this study provide strong empirical evidence supporting the critical role of behavioral engagement in determining academic success within online learning environments. The findings always show that students with increased rates of interaction, in terms of participation, use of resources, and discussion, have better academic performance. These results support the idea that engagement is not an auxiliary feature of the learning process but one of the key elements that have a direct impact on student performance in a digital learning environment.

Moderate to high variability in engagement behaviors was observed in the descriptive analysis, indicating that there is a significant dissimilarity in the ways students engage with online learning systems. This difference is noteworthy because it shows that not every learner receives the same level of advantages in digital environments, and engagement rates could serve as a distinguishing factor in academic achievement. This is further evidenced by the distribution of the levels of performance, with most of the students being in the medium category, which would be approached by improved methods of engagement.

The correlation analysis gives clear evidence of positive relationships among behavioral engagement indicators and academic performance. Specifically, the close relationship between the use of resources and academic performance implies that those students who actively read and use learning resources have a higher probability of doing well. This is consistent with the results of Broadbent and Poon (2015), who found that self-regulated learning strategies such as active resource engagement are significant predictors of academic achievement in an online environment (Broadbent & Poon, 2015; Park & Choi, 2009). Likewise, there was a positive correlation between raised hands and discussion participation and performance, showing that engagement in learning activities leads to improved performance. These findings go along with the findings of earlier studies that have underscored the significance of interactive learning conditions with regard to facilitating student achievement (Hrastinski, 2009; Richardson et al., 2017).

These findings are further reinforced by the ANOVA results, which show that there are significant differences in the level of engagement among the performance groups. High performers had significantly higher engagement scores than low performers. This indicates that engagement not only correlates with performance, but it can also be used as a distinguishing factor between varying degrees of academic performance. This fact is consistent with the findings of Carini, Kuh, and Klein (2006), who established that academic performance and learning outcomes of student engagement are closely related in different learning environments (Carini et al., 2006; MOORE, 2013).

The regression analysis gives more insights into the predictive capacity of particular engagement behaviors. Among all the variables that were analyzed, visiting resources and raising hands were the most important predictors of academic success, and the discussion participation had a smaller but significant impact. Interestingly, performance was not significantly predicted by the announcements seen, which means that passive types of engagement are not as influential as active engagement. Such a difference between active and passive engagement has been emphasized in previous research, which indicates that meaningful interaction and engagement are more efficient in improving the learning outcomes than passively consuming content (Chi & Wylie, 2014; Macfadyen & Dawson, 2010; Sun et al., 2008).

On the whole, the findings indicate that behavioral engagement is a multidimensional construct whereby various forms of interaction make varying impacts on academic success. The strategies of active engagement, including participation and resource utilization, seem to have a higher level of influence on performance, whereas passive engagement might not have a considerable effect. The present finding supports the need to create online learning environments that promote student interaction and participation.

The results of this study are mostly congruent with other studies on student engagement and academic success in comparison to the existing literature. Nevertheless, the research builds on existing literature since it uses a secondary dataset obtained through an LMS and implements Python-based analytical tools to give a more factual and objective assessment of engagement behaviors. This study will provide a better depiction of engagement patterns as opposed to other studies that use self-reported data because the study captures real student interactions. This helps to expand the area of learning analytics, which accentuates the utilization of data in enhancing educational results (Ferguson, 2012; Zimmerman, 2002).

Although it has made its contributions, there are several limitations to this study. To begin with, the secondary data utilized in Kaggle does not allow for control of the data collection process, and thus, it might interfere with the external validity of the results in other learning environments. Second, academic performance is used as a categorical variable (low, medium, high), which had to be numerically coded to be used in regression analysis. Whereas this method is methodologically acceptable, it might not capture all the intricacies of academic achievement. Third, the dataset lacks the psychological or

motivational factors, i.e., the student attitudes or self-efficacy, that can affect both engagement and performance as well. Lastly, the cross-sectional data restricts the opportunity to draw a cause-and-effect relationship between engagement and academic success.

These limitations should be overcome in future studies by including longitudinal data to analyze the evolution of the patterns of engagement over time and the effects on academic outcomes. Also, the combination of psychological constructs and qualitative data may offer a more in-depth insight into student behavior in online learning conditions. To enhance the predictive accuracy of engagement-based models, researchers can also consider more sophisticated methods of analysis, including machine learning models. Moreover, the generalizability of findings would be improved by conducting comparative research across various educational systems and cultural backgrounds, and would help to gain a more comprehensive perspective on the importance of engagement in education.

To sum up, the paper has identified that behavioral engagement has a tremendous effect on academic success in online education. The results highlight the significance of active learning, the use of resources, and interactive learning in improving the performance of the students. Using real-life data and computational analysis, the study aids in the comprehension of the impact of the student interaction patterns on the learning outcomes and offers the practical implications that can be utilized to enhance the practices of online education.

## 5. Conclusion

This research offers solid empirical support that behavioral engagement is an important factor in determining academic achievement in an online learning setting. Through the analysis of the patterns of interaction among students based on structured data, the results reveal that active engagement behaviors, especially those that concern resource use and engagement, have a major impact on academic performance. The findings are always the same; active engagement with learning resources and involvement in academic processes yield better results as students are more likely to perform better in comparison to the less active learners. Another aspect that the study emphasizes is the need to differentiate between active and passive engagement. Although actions like checking announcements help in raising awareness, they cannot predict the success in academics with any substantial degree of accuracy compared with more interactive types of engagement. This underlines the importance of teachers and schools in creating learning spaces that promote active engagement and not passive learning. Although there are some limitations, such as the use of a secondary dataset and performance measures in categories, the study provides useful information about the behavior of students in a digital learning environment. The analysis is also based on Python, which enhances the reliability and reproducibility of findings. In general, this study adds to the emerging area of learning analytics and suggests practical implications to enhance student interaction and academic performance related to online learning.

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