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Exploring key parameters influencing student performance in a blended learning environment using learning analytics

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Abstract

Understanding the factors that influence students' results in hybrid learning environments is becoming increasingly important in today's educational environment. The goal of this research is to examine factors that influence students' academic performance as well as their level of participation in blended learning environments. A comprehensive study was conducted with 330 interested participants from the prestigious government polytechnics of the state of Karnataka in order to achieve this goal. Our data acquisition approach relied on the administration of a meticulously crafted survey questionnaire. The conceptual framework underpinning this study seamlessly integrates Transactional Distance Theory (TDT) principles with valuable insights derived from prior research. The Welch test and one-way ANOVA (Analysis of Variance) are two statistical approaches that we used selectively to reinforce our research which produced surprising results. These findings underscore the pivotal role played by certain specific factors. The geographical location of learners and the medium through which they pursue their studies have emerged as critical determinants significantly influencing academic performance. Aspects like the frequency of login activities and active engagement in forum discussions have been found to exert a positive influence on learners' academic performance. In contrast, the duration of sleep did not show a significant impact on performance. These insights bear tangible implications for teachers and policymakers who are dedicated to the enhancement of the quality of BL programs with the ultimate goal of enriching the overall educational experience.

Keywords: Academic achievement, Blended learning, Learner performance, Learning analytics, Online learning platforms, Student engagement, Transactional distance theory.

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Contents

Contribution of this paper to the literature
This research innovatively crafts a dataset tailored to regional student populations which significantly enhances the accuracy of machine learning models within the local context. It diverges from the norm of single-course analysis instead delving into overall academic performance influenced by a diverse blend of socio-economic, technical and lifestyle variables.

1. Introduction

Blended learning (BL) is increasingly recognized for its role in enriching student engagement and bolstering educational outcomes. BL provides a versatile approach that can be tailored to meet the varied needs and learning styles of students by integrating face-to-face teaching with online educational activities (Horn & Staker, 2011). Concurrently, the field of learning analytics (LA) has become a vital component for enhancing the effectiveness of BL by using data-driven insights (Jovanovic, Gasevic, Dawson, Pardo, & Mirriahi, 2017). LA explores the knowledge collected through students' interactions on digital platforms particularly those found in learning management systems (LMS). It reveals underlying factors that influence academic success by analyzing data from multiple sources including student backgrounds, content interaction and engagement with online resources. This analysis helps in identifying behavioral patterns and trends which can inform teaching strategies and facilitate specific educational interventions.

TDT serves as a significant model for examining determinants of student success within the scope of technical education especially when integrated with learning analytics (LA). According to this concept, a crucial component of teaching efficacy and student achievement is transactional distance which is defined as the cognitive and communicative space between students and teachers (Moore, 1993). TDT provides a strong foundation for research into how factors like technology use, instructional design and teacher feedback affect this transactional space and student outcomes in technical education fields. TDT equips researchers with a theoretical framework to formulate hypotheses and construct research designs that examine the complex dynamics between educational factors and student achievement, leveraging LA's advanced tools. For example, investigations might examine the influence of personalized, timely feedback from teachers, facilitated by LA tools, on minimizing transactional distance and improving student outcomes (Jovanovic et al., 2017). Additionally, research could be directed to understand if the incorporation of interactive digital content and simulation-based learning in curriculum can stimulate student engagement, diminish transactional distance and favorably affect their achievements.

The aim of this study is to investigate the factors that impact technical education achievement from a LA perspective with an emphasis on data collected from Karnataka's Learning Management System (LMS) users. The research follows the principle of TDT. This research builds upon existing literature to examine the relationship between student performance and variables including the geographical location of the student, mode of instruction, sleeping habits, the regularity of LMS access and participation in online discussions. It also probes the impact of the time spent on online lectures on students' academic results. This study improves our understanding of BL and its impact on learning outcomes by combining the analytical effectiveness of LA with well-established pedagogical concepts. The research poses the following research questions (RQ) to guide the inquiry:

RQ 1: Does learners' background like residing geographical area and medium of study affect academic performance?

RQ 2: To what extent do factors like the frequency of learners' LMS logins, their engagement in discussion forums and the duration of online lecture viewing impact their academic performance?

RQ 3: Is there a relationship between the duration of students' sleep and their academic achievement?

2. Literature Review

Kintu, Zhu, and Kagambe (2017) have tried to find out the relationship between learners' characteristics, outcomes associated with the learning process and the design features of the learning systems. Data from 238 participants were used for the above study. The researchers have used the results of the final examination for measuring their performance. Multiple regression analysis was used to analyse the study findings. The results showed that a number of BL design features including the calibre of the technology used, different online tools and personal interactions as well as student characteristics like attitude and self-control were good predictors of learners' satisfaction levels. The study offers valuable insights into the complex dynamics of learner satisfaction within BL contexts. However, it's important to remember that student satisfaction is only one aspect of the learning process, and future studies may examine how it interacts with academic success.

Zhao et al. (2020) investigated the prediction of academic performance using behavioral data. The researchers aimed to gain a thorough understanding of the factors that contribute to both high and low academic performance by analyzing metrics that capture linear and non-linear behavioral changes in campus lifestyles such as regularity and stability. They employed long short-term memory (LSTM) to extract features that represent the dynamic changes in temporal lifestyle patterns. It is important to mention that certain factors such as peer influence and sleep were not considered in their study. This data-driven approach to predict academic performance presents a significant step in educational research. Future studies could consider the inclusion of factors like peer influence and sleep to create a more comprehensive model.

Taghizadeh and Hajhosseini (2021) explored the perceptions, communicative dynamics and contentment among master's students engaged in BL. The study's aim was to discern the impact of these factors on overall student contentment. Participants included 140 master's candidates from the virtual campus of Iran University. The investigation used a quartet of surveys designed to gauge student contentment, viewpoints, interaction modalities and pedagogical excellence. Findings from multiple regression analysis indicated that the quality of instruction was a more prominent determinant of student contentment than either interaction or attitudes. This outcome highlights the critical importance of equipping educators with the skills necessary for proficient online instruction. This research underscores the pivotal role of teaching in shaping student satisfaction within BL. However, a deeper exploration of various aspects of interaction patterns and attitudes could provide a more nuanced understanding.

Sweller, Ayres, Kalyuga, and Chandler (2003) explored how student dispositions, amount of rest, timing of assessments and levels of vigor influenced the results of engineering students in virtual evaluations. They used statistical procedures, including two sample t- tests and ANOVA to scrutinize the data. According to the research, students often performed best in morning sessions when they were in positive moods. It is suggested that a wider range of academic disciplines and student backgrounds be included in order to increase the relevance of the research.

Wei, Shi, MacLeod, and Yang (2022) examined the key parameters that impact students' academic ability in a hybrid learning environment considering personal abilities, social skills and the differences in their learning environments. The study collected data from 366 participants through a survey questionnaire from a university's students located in China. Hierarchical regression applied to this sample data revealed intrinsic motivation of a student, extrinsic motivation conditions support from the instructor, performance expectancy and good facilitating conditions have a considerable impact on the ability of a learner in a blended learning setup. Future research could probe deeper into the interplay of these factors and their contextual significance.

Li and Xue (2023) explored the determinants influencing learner engagement in various higher education contexts. They found 14 different elements that contribute to students' active engagement in their academics by using a comprehensive meta-analysis. These factors were classified into two categories: promoting factors and hindering factors. The promoting factors encompassed elements such as students' positive emotions, their learning behaviors, teacher-student interactions, the quality of teacher-student relationships and partnerships, students' cognitive abilities, the availability of supportive learning resources and individual personality traits. On the other hand, hindering factors included the absence of environmental support, negative student conduct and adverse teacher behaviors. These results provide important information on various elements that might either increase or decrease student engagement in higher education environments. The categorization of these factors is particularly useful in understanding their dynamics and planning effective interventions.

Moreno-Marcos, Muñoz-Merino, Alario-Hoyos, Estévez-Ayres, and Delgado Kloos (2018) examined the predictive ability to anticipate grades using data files obtained from the online learning platform. The study incorporated a range of predictor variables including forum engagement, exercise completion, video consumption and prior academic performance. The findings indicated that earlier assignments were more challenging to predict accurately. Moreover, the study revealed that the prediction outcomes were more influenced by the data itself than the specific machine learning (ML) algorithm employed as there was no significant difference in performance among different ML algorithms. It was also observed that predicting the outcomes of close-ended assignments proved to be comparatively more straightforward than those of open-ended assignments. The results suggest that timely predictions can serve as a valuable tool for identifying students who may be at risk and implementing targeted interventions to support them in reaching their academic objectives.

Moreno-Marcos, Pong, Muñoz-Merino, and Kloos (2020) examined the impact of different factors on the prediction of learners' performance. These parameters included students' grades in previous exams, variables related to forum discussions, assignment-related variables, click-stream data associated with the usage of learning systems, the duration of the course, the kind of assignments used in the course, procedures used in data collection, the format of the questions used in the examination and final grades. The researchers analyzed data from two MOOCs offered by Universidad Carlos III de Madrid (UC3M) and Hong Kong University of Science and Technology (HKUST). In their future work, the authors suggested exploring additional factors such as the particular area of the course, the system used to evaluate the participants (including midterm and final exam grades) and the type of exam questions to assess their impact on predictive power. Furthermore, the authors emphasized the importance of developing systems that use these predictions to inform instructors and learners. Improvements in success rates within MOOCs can be achieved by leveraging predictions effectively. However, a deeper exploration of specific predictive variables could refine the predictive model.

Abuhassna et al. (2020) carried out a research study to find out the potential parameters affecting students' academic accomplishments and satisfaction within an online learning platform. The study encompassed a sample of 243 online learners with data collection conducted through the distribution of questionnaires. The researchers developed a theoretical framework based on TDT to assess student satisfaction and they used Bloom's theory to measure academic success. The results indicate that there is a requirement for more in-depth research concerning the relationship between the complexity of online learning platforms and the Technology Acceptance Model (TAM). Additionally, it is essential to explore how these factors interact within blended learning environments.

Ahuja, Kaur, and Panda (2019) have tried to identify the parameters that contribute to the effectiveness of e-learning in educational settings in India. The researchers used data mining techniques to investigate the log file dataset from an online course. The analysis took into account various parameters including the frequency of student logins, engagement in online discussions, message posting and reading, checking of online materials and the overall grade achieved. The application of clustering algorithms revealed that aspects associated with prompt content verification and uploading positively impacted students' learning. In contrast, the decision pointed out that meeting assignment deadlines, coupled with the practice of reviewing online content and actively engaging in message posting, substantially contributed to improving students' academic performance. These findings highlight the significance of timely engagement with online course materials and active participation in assignments and discussions for successful online learning outcomes.

Dubey, Piroska, and Gautam (2019) found that early learner dropout rates on e-learning platforms can be attributed to factors such as poor content quality, distractions, outdated information and detraction factors. They highlighted significant factors such as financial concerns, content quality, technological difficulties and impediments related to language competency in order to overcome these challenges and improve student motivation. This work strongly advocates for the localization of MOOCs. Table 1 shows a summary of key publications used in the work.

Table 1. Summary of key publications.

Author	Objectives	Limitations
Kintu et al. (2017)	To find the impact of learner characteristics and design features on student satisfaction and outcome in BL.	The study found that none of the independent variables examined in the research were identified as significant standalone predictors of students' performance.
Ahuja et al. (2019)	To discern the parameters that contribute to the enhanced adoption of virtual learning.	The utilization of data solely from a 'Data Structure' course constrains the ability to generalize findings to other contexts.
Abuhassna et al. (2020)	To improve students' online learning experience in terms of academic achievements and overall satisfaction.	The research will not incorporate blended learning environments into its investigation.
Kaur, Kumar, and Kaushal (2021)	To examine how mood, energy levels, sleep duration and time of day impact the academic achievement of engineering learners during online examinations.	The dataset is considered very small with only 120 students. Only mood and emotion are considered for performance.
Moreno-Marcos et al. (2020)	To explore the determinants affecting the forecasting of learners' academic performance through the use of LA	Insufficiency in data regarding learners' offline behaviour.
Zhao et al. (2020)	To predict academic performance by using behavioural data as a predictive factor.	Features (e.g., peer effect and sleep) were not considered in the study.

3. Contribution

The contribution of this study lies in the creation of a novel dataset specifically focused on regional students which significantly enhances the applicability and accuracy of machine learning models within the local context. This research investigates the entire academic performance of students unlike previous studies that primarily focused on single-course performance. It encompasses a comprehensive range of factors including socio-economic aspects such as residential geographical area and medium of study, technical elements like learner-digital environment interaction and learner-learner interaction as well as lifestyle parameters such as sleep duration. The study aims to provide in-depth insights into the determinants that influence learners' performance in a holistic manner by considering this multifaceted set of variables. This distinctive approach adds to the existing knowledge base and enhances the comprehension of the intricate dynamics that influence academic performance.

4. Significance of the Study

This study addresses a crucial gap by exploring what makes BL successful or unsuccessful, giving teachers and policymakers useful information. These insights empower them to craft tailored, effective BL programs that boost student outcomes and enrich engagement. This research provides the foundation for strategies that indicate improved learning outcomes such as increased academic achievement, increased skill development and an overall improvement in student performance through the identification of the variables affecting academic success. In addition, the study offers a deep dive into student engagement and retention which are pivotal for a more rewarding learning experience.

5. Methodology

This section offers a detailed insight into our research methodology, presenting a well-structured description of the data collection procedures, the variables under scrutiny and the statistical analyses applied to investigate our hypotheses.

5.1. Participants

Data for this study was gathered through a questionnaire that aimed to capture information regarding diverse factors that could potentially impact the performance of technical students in BL. The questionnaire used in this research was tailored to align with the study's hypothesis and encompassed demographic and behavioral aspects. The survey was distributed among a sample of Karnataka's government diploma students to assess their utilization of the Karnataka Learning Management System (LMS).

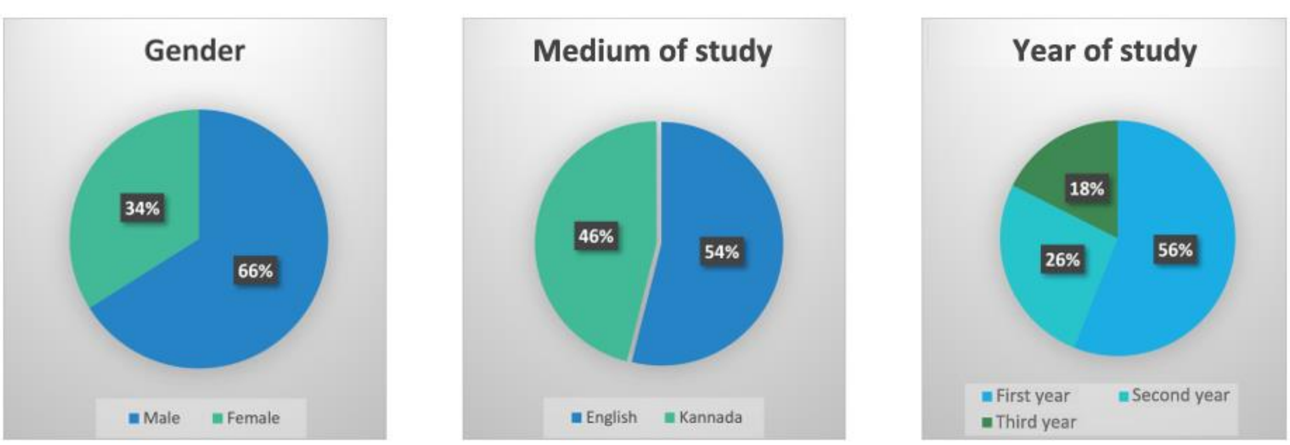


Figure 1. Demographics details.

Content validity methodology was used to test the survey questionnaire. We received 386 responses voluntarily and after eliminating outliers, we retained 330 responses. According to the responders' demographic information in Figure 1, their ages ranged from 18 to 22. Among them, 218 were male and 112 were female. Regarding language medium, 178 used English while 152 used Kannada. In terms of academic year, 185 students were in their third year, 87 in their second year and 58 in their first year of study. Data was collected from Karnataka Government Polytechnic students on their Learning Management System (LMS) usage. Every semester, students are provided with online content for all the subjects they have for their academics. Data pre-processing was done to clean and transform data for further analysis. Some questionnaires followed a five-point Likert scale whereas some were categorical.

5.2. Hypothesis Development

The concept of TDT first introduced by Moore (1993) focuses on the potential for psychological and communication gaps to develop between students and teachers in educational environments. It also introduces the idea of "transactional distance," which refers to the perceived distance or separation that a student and teacher may feel from one another. TDT highlights three essential elements: dialogue, structure and learner autonomy which play a significant role in minimizing transactional distance. Effective dialogue involves interactive communication, feedback and support enabling learners to actively engage with teachers. This interaction fosters a sense of connection and helps bridge the psychological gap. Well-structured courses are vital in reducing ambiguity and facilitating learner comprehension. Clear instructions, learning objectives and logically sequenced content contribute to a structured learning environment. Such structure promotes a better understanding of the course materials, reducing the perceived distance between learners and instructors. Learner autonomy is another crucial element emphasized by TDT. By promoting student autonomy, TDT empowers learners to assume control over their learning journey enabling them to make decisions concerning their goals, pace and preferred learning methods. This shift towards learner self-direction and engagement with educational materials leads to a reduction in transactional distance. The aforementioned decrease is quite valuable as it contributes to the improvement of the educational process and results. Students are more inclined to actively participate in the learning process and accomplish higher academic goals when they have a sense of autonomy, face well-defined course frameworks and feel linked to their teachers. Teachers can also minimize transactional distance by fostering regular and meaningful interaction providing clear and organized course materials and promoting learner autonomy through activities that encourage self-reflection and decision-making. Technology plays a significant role in reducing transactional distance in distance education and online learning environments. Online communication tools such as discussion forums and video conferencing facilitate dialogue and interaction, bridging the gaps between learners and teachers. However, it is important to note that technology alone does not automatically reduce this distance. Moore (1993) stresses the necessity of aligning technology with the principles of TDT to effectively support communication and collaboration in educational settings.

TDT had a profound impact on the design of online courses, instructional strategies and the development of technologies in distance education. Teachers aim to provide educational environments that facilitate productive discourse, offer unambiguous structure and encourage learner autonomy by implementing the TDT principles. This approach ensures that learners experience reduced transactional distance leading to enhanced learning experiences and improved academic outcomes (Moore & Kearsley, 2011). This research puts forward the following hypothesis:

H_1: Learners' geographical area (rural or urban) affects their academic outcomes.

Research studies consistently demonstrate that learners' academic achievements in BL settings are noticeably impacted by their geographic location specifically whether they reside in rural or urban areas (Panizzon, 2015). TDT serves as an invaluable theoretical framework for understanding this correlation. Several factors contribute to this phenomenon including limited access to educational resources, disparities in technology infrastructure and the existence of a digital divide (Rafi, JianMing, & Ahmad, 2019). Furthermore, discrepancies in the quality of teachers and the accessibility of support services between rural and urban areas also play a role in the observed disparities in academic outcomes. The combination of limited resources, unequal access to technology and variations in instructional support creates a higher level of transactional distance for rural learners which directly affects their engagement levels and overall academic success in blended learning environments.

H_2: The language of instruction in learners' high school education influences their academic achievement.

A strong command over the medium of instruction is crucial for success in technical education especially in institutions where English serves as the primary language of instruction. Proficiency in the chosen medium of study significantly impacts the learner's ability to comprehend and actively engage with academic content. The language with which the student feels most comfortable in their matriculation medium has an impact on this competency. When the learners' matriculation medium aligns with the language used in online learning materials, it reduces cognitive load and allows learners to concentrate on understanding and internalizing the course content. Moreover, a familiar matriculation medium empowers learners, enhancing their autonomy and control over the learning process. These factors collectively contribute to improved academic performance in online learning by removing barriers between learners and teachers facilitating effective communication, promoting comprehension and fostering engagement.

H_3: Learners' performance is related to how long they sleep.

In a study conducted by Dewald, Meijer, Oort, Kerkhof, and Bögels (2010) involving adolescents, it was discovered that obtaining sufficient sleep duration correlated with better academic performance compared to those experiencing insufficient sleep. Furthermore, a meta-analysis conducted by Gruber, Wiebe, Wells, Cassoff, and Monson (2010) which encompassed multiple studies revealed a positive relationship between sleep duration and academic achievement in children and adolescents. Sleep deprivation can lead to reduced attention, impaired concentration and decreased cognitive abilities as highlighted by Hirshkowitz et al. (2015). These conditions contribute to an increased transactional distance making it more challenging for learners to engage with instructional materials, comprehend concepts and actively participate in the learning process. Additionally, sleep plays a crucial role in memory consolidation as emphasized by Diekelmann and Born (2010). During sleep, memories are consolidated and integrated into long-term storage, facilitating better retrieval and application of learned information. Insufficient sleep disrupts this memory consolidation process resulting in reduced retention and impaired academic performance. Therefore, it is evident that adequate sleep is crucial for optimal cognitive functioning, memory consolidation, attention, effective learning and academic achievement.

H_4: Regular login will increase the chances of learners' performance and success rate.

Regular login into the online learning system is widely acknowledged as a crucial element that contributes significantly to learners' performance and success in BL. Consistently engaging through regular login allows learners to stay informed about course updates and promptly access learning resources. It also enables them to adhere to assignment deadlines, effectively manage their time and complete tasks on time. Additionally, regular login provides learners with access to instructor support allowing them to seek guidance and clarification whenever necessary. Learners may enhance their academic performance and improve their chances of success in mixed learning environments by making the most of these benefits. Regular login promotes consistent engagement, leading to a better understanding of course content and enhanced application of acquired knowledge thereby reducing the sense of distance between learners and teachers.

H_5: Forum interaction has a positive effect on the academic outcome of a learner.

Forum interactions have been shown to positively impact learners' academic performance by fostering active participation, engagement and the sharing of perspectives. Rovai (2002) and Arbaugh (2002) conducted studies that demonstrated a relationship between increased learner engagement and improved academic performance. Learners' experience a sense of social presence, feeling connected and supported by their peers participating in forum discussions (Lee & Recker, 2021). Picciano (2002) and Shea, Li, Swan, and Pickett (2005) conducted research highlighting the positive relationship between social presence and enhanced academic performance. Engaging in forum interactions provides learners with opportunities for collaborative learning, expressing their thoughts and receiving feedback from peers. This type of interaction has been associated with cognitive development, critical thinking skills and a deeper understanding of the subject matter. Harasim (1995) and Garrison, Anderson, and Archer (2001) conducted studies that demonstrated the positive impact of collaborative learning and critical thinking on academic achievement. Active participation in forum discussions also promotes effective communication skills such as articulating thoughts, expressing ideas clearly and providing constructive feedback. These communication skills are transferable to various academic tasks including writing papers, delivering presentations and engaging in academic debates. Shea et al. (2005) conducted research that showed a positive relationship between online communication skills and academic performance. Furthermore, forum interactions facilitate knowledge construction as learners share diverse perspectives, exchange ideas and challenge assumptions. This process supports deep learning which involves integrating new information with existing knowledge frameworks.

H_6: Learners experienced improved academic achievements by spending extra time on online lectures.

Spending a greater length of time watching online lectures reflects learners' engagement and commitment to the learning process. This active involvement plays a significant role in bridging the psychological gap by fostering a sense of connection, focus and dedication to the course content. Consequently, learners who allocate more time to viewing online lectures are more likely to experience improved academic outcomes. Empirical research studies such as those conducted by Bernard et al. (2004) have consistently found a positive relationship between increased time dedicated to learning tasks and academic performance. Increasing the time invested in online lectures allows learners to engage more deeply with the course material, review concepts and clarify their understanding. This extended engagement facilitates interaction between learners and the instructional content thereby reducing the transactional distance. Previous research by Sweller et al. (2003) has demonstrated the beneficial effects of repeated exposure and distributed practice on knowledge acquisition and retention ultimately leading to improved academic outcomes. Online lectures offer the advantage of self-paced learning allowing learners to control the speed and timing of their engagement with the content. This autonomy empowers learners to allocate more time to challenging topics or review materials as needed. Moreover, dedicating more time to viewing online lectures facilitates deeper cognitive processing. This extended engagement promotes reflection, analysis and the development of more intricate mental representations. Dedicating more time to viewing online lectures boosts students' comprehension, engagement and cognitive processing leading to better academic results.

5.3. Tests Employed for Hypothesis Testing

It is crucial to consider the specific characteristics of the data, the research design and the assumptions associated with each statistical test when selecting appropriate tests. It appears suitable to use Welch's test, a combination of the t-test and ANOVA given the nature of hypotheses and the possible variations in variances or means between groups. There are various methods to test hypotheses in statistical analysis apart from Welch's test and ANOVA as shown in Table 2.

The methods used in our study to verify our hypothesis are listed in Table 3. Welch's test is an appropriate statistical method for hypothesis testing 1 and 2 considering that we have two or more groups with unequal variances. On the other hand, ANOVA is a suitable choice for hypotheses 3 to 6 as it enables the comparison of means across three or more groups.

These hypotheses involve factors such as sleep duration levels per day, frequency of login, level of activity in discussion forums and viewing time of online lectures. ANOVA allows determining if there are statistically significant differences in academic performance across these groups. It offers insights into the potential influence of different factors such as sleep duration, login frequency, participation in discussion forums and the time spent on online lectures on academic outcomes.

Table 2. Methods to test hypotheses in statistical analysis.

Test	Description	Application
T-test	Compares the means of two independent groups.	Used when comparing means between two distinct groups.
Chi-square test	Assesses the association between categorical variables.	Examines the relationship between two categorical variables.
Regression analysis	Examines the relationship between dependent and independent variables considering their respective characteristics and assumptions.	Predicts the value of the continuous dependent variable based on the independent variables.
Pearson correlation	Assesses the magnitude and direction of the association between continuous variables.	Determines the degree of relationship between two continuous variables.
Mann-Whitney U test	Non-parametric test for comparing the distributions of two independent groups.	Appropriate when data violate assumptions of normality or for non-parametric or ordinal data.
Kruskal-Wallis test	Non-parametric test for comparing distributions of three or more independent groups.	Used when assumptions of ANOVA are violated or for non-parametric data.

Table 3. Methods used to test hypotheses.

Hypothesis	Variables	Groups	Justification for the test
1	Geographical area	Rural and urban	Welch's test is suitable when comparing the impact of groups (Geographical areas) with unequal variances.
2	Medium of study	English and Kannada	Welch's test is appropriate when comparing the impact of groups (Medium of study) with unequal variances. Academic performance in different mediums of study may have varying levels of variance due to factors such as language proficiency, resources or instructional methods.
3	Sleep duration	Less than 5 hours, 6 hours, 7 hours and 8 hours or greater than 8 hours.	ANOVA is suitable for comparing the means of three or more groups (Sleep duration levels). It helps determine if there are statistically significant differences in academic performance across these groups providing insights into the impact of varying sleep durations on academic outcomes.
4	LMS login frequency	Regularly, often, sometimes and never.	ANOVA allows comparing the means of three or more groups (Login frequency levels) to determine if there are significant relationships with academic performance. It helps assess the impact of varying login frequencies on academic outcomes.
5	Forum activity frequency	Always, often, sometimes, rarely and never. '	ANOVA enables comparing the means of three or more groups (Activity frequency levels) to assess their impact on academic results. It helps to determine if participants who actively engage in discussion forums exhibit higher academic performance.
6	Online lecture viewing frequency	Always, often, sometimes, rarely and never.	ANOVA is appropriate for comparing means of three or more groups (Viewing frequency levels) to evaluate their impact on academic outcomes. It assists in finding out whether learners who devote more time to watching online lectures obtain higher academic outcomes.

5.4. Procedure

Algorithm 1: Statistical Analysis of Hypotheses
Input: Academic performance dataset Output: Hypothesis test results.

1) Pre-process the data (handle missing values, convert categorical variables and perform data transformations).
2) Define null and alternative hypotheses.
3) Set the significance level (α) to 0.05.
4) For each hypothesis, do the following:
    a) Specify the variables and groups for the hypothesis.
    b) Conduct necessary data grouping and transformations based on the hypothesis.
    c) If the hypothesis requires Welch's test, do the following:
        i) Apply Welch's test to compare the means of the groups that have different variances.
        ii) Calculate the test statistic and degrees of freedom specific to Welch's test.
        iii) Determine the p-value corresponding to the obtained test statistic.
        iv) If the calculated p-value $< \alpha$, reject Ho and conclude that there is a significant relationship between the variables. Otherwise, fail to reject the Ho and conclude that there is no statistically significant relationship between the variables under investigation.
    d) If the hypothesis requires ANOVA, do the following:
        i) Apply ANOVA to compare the means of the groups.
        ii) Compute the F-statistic and degrees of freedom.
        iii) Determine the p-value associated with the F-statistic.
        iv) If the p-value $< \alpha$, reject the Ho, otherwise, fail to reject the Ho and conclude that there is no significant relationship between the variables.

Algorithm 1 aims to analyze an academic performance dataset and perform hypothesis tests to determine the presence of significant relationships between variables. The algorithm starts by preprocessing the data and defining the null hypothesis (Ho) which represents the assumption of no relationship or difference and the alternative hypothesis (Ha) which presents the claim that there is a significant relationship or difference to be considered. The significance level is set to 0.05 which is a standard threshold in statistical analysis. It then proceeds to evaluate each hypothesis individually conducting appropriate data transformations and applying either Welch's test or ANOVA. Welch's test is used when comparing means of groups with unequal variances while ANOVA is employed for comparing means of multiple groups. By calculating test statistics, degrees of freedom and p-values, the algorithm determines if the null hypothesis should be rejected or not. This algorithm provides valuable insights into the relationships among variables in the academic performance dataset. The ANOVA formula components are summarized in Table 4 and the formula used for the Welch test is as follows:

$$t = \frac{\bar{b}_1 - \bar{b}_2}{\sqrt{\left(\frac{d_1^2}{r_1}\right) + \left(\frac{d_2^2}{r_2}\right)}}$$

- Where t is the test statistic.
- $\bar{b}_1$ and $\bar{b}_2$ are the sample means of groups 1 and 2.
- d_1 and d_2 are the sample standard deviations of groups 1 and 2.
- r_1 and r_2 are the sample sizes of groups 1 and 2.

The formula for the sample standard deviation is

$$d = \sqrt{\frac{\sum(b_i - \bar{b})^2}{r-1}}$$

- where b_i denotes each individual value in the sample.
- $\bar{b}$ denotes the sample mean.
- r denotes the sample size.
- Σ denotes the summation symbol.

The degrees of freedom for Welch's test are calculated using the following formula:

$$\text{Degrees of freedom} = \frac{\left(\frac{d_1^2}{r_1} + \frac{d_2^2}{r_2}\right)^2}{\frac{\left(\frac{d_1^2}{r_1}\right)^2}{r_1-1} + \frac{\left(\frac{d_2^2}{r_2}\right)^2}{r_2-1}}$$

Table 4. ANOVA formula component.

Component	Formulas
Total sum of squares (TSS)	TSS = BGSS + WGSS
Between-group sum of squares (BGSS)	BGSS = $\sum n_{i^*}(\bar{X}_i - \bar{\bar{X}})^2$
Within-group sum of squares (WGSS)	WGSS = $\sum(X_j - \bar{X}_i)^2$
Total degrees of freedom (TDF)	TDF = N – 1
Between-group degrees of freedom (BGDF)	BGDF = k – 1
Within-group degrees of freedom (WGDF)	WGDF = N – k
Mean square between (MSB)	MSB = BGSS / dfb
Mean square within (MSW)	MSW = WGSS / dfw
F-statistic	F = MSB / MSW
Number of groups (k)	The total number of groups in the study
Number of observations (N)	The total number of observations in the study
Mean of the i^{th} group ($\bar{X}_i$)	The average value of the i^{th} group
Overall mean of all groups ($\bar{\bar{X}}$)	The average value across all groups

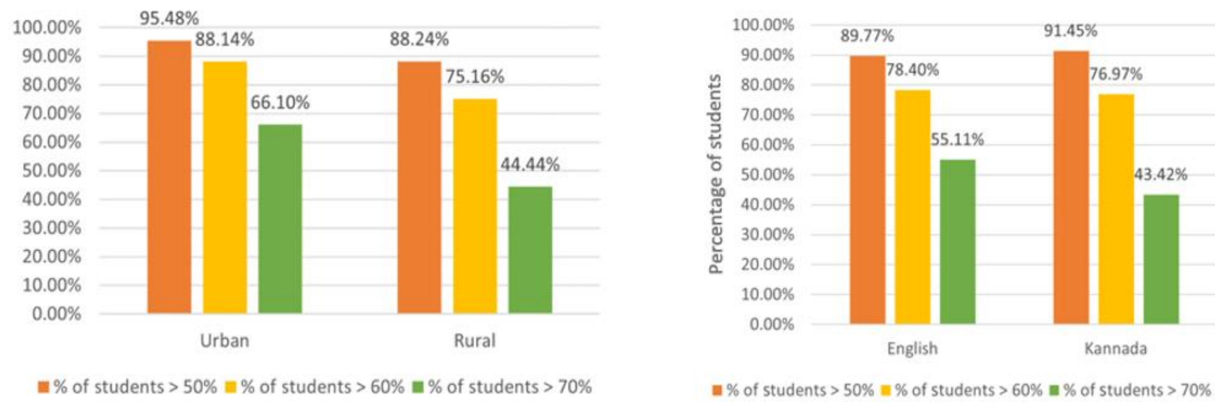
6. Results and Discussion

H_1: Learners' geographical area (rural or urban) affects their academic outcomes.

In this study, the null hypothesis (Ho) proposes that the geographical area where learners reside does not significantly impact their academic outcomes. On the other hand, the alternative hypothesis (Ha) suggests that the geographical area of residence does have a significant influence on learners' academic outcomes. The findings depicted in Figure 2a indicate that a greater proportion of students from urban areas scored exceeding 50%, 60% and 70% compared to rural students. 95.48% of city learners scored above 50% while only 88.24% of rural learners reached this threshold. Similarly, 88.15% of urban learners achieved scores above 60% whereas only 75.15% of rural learners did so. This pattern persisted for scores exceeding 70% with 66.1% of urban students surpassing this mark in contrast to 44.44% of their rural counterparts. Table 5 presents the mean scores showing that the mean for urban areas is higher at 75.29 compared to rural areas. The analysis conducted using the Welch test demonstrated a statistically significant difference in means with a test statistic of 0.0 below the predetermined significance level set at 0.05 rejecting the null hypothesis (Ho) in favor of the alternative hypothesis (Ha) indicating a significant difference in scores between rural and urban areas. These findings suggest that educational institutions should consider providing additional support and resources tailored to the specific needs of learners from rural areas to bridge the performance gap.

Table 5. Results of the impact of geographical distribution.

Parameters	Sub classification	Sample	Mean	Standard deviation	Method used	T value	P value	Hypothesis
Geographical area	Rural	153	67.73	15.89	T- test	-4.7	0.0	Accepted
	Urban	177	75.29	13.46				



(a) Geographical distribution (b) Medium of study

Figure 2. Impact of geographical area and medium of study on academic performance.

H_2: The language of instruction in learners' high school education influences their academic achievement.

In this study, the null hypothesis (Ho) states that the learners' matriculation medium of study does not have a significant impact on their academic outcomes. In contrast, the alternative hypothesis (Ha) proposes that the medium significantly influences their academic outcomes. As illustrated in Figure 2b, a higher proportion of students educated in the English-medium (78.40%) scored above 60% compared to those who have completed their matriculation in Kannada (76.97%). Furthermore, there was a notable difference in higher scoring brackets with 55.10% of English-medium students surpassing the 70% mark as opposed to 43.43% of students from Kannada backgrounds. This disparity is further highlighted in Table 6 where the average scores of English medium students exceeded those of Kannada-medium students. A Welch test was applied to rigorously analyze these differences revealing a statistically significant variance in mean scores between the two groups as evidenced by a t-value of -3.2 and a p-value of 0.002.

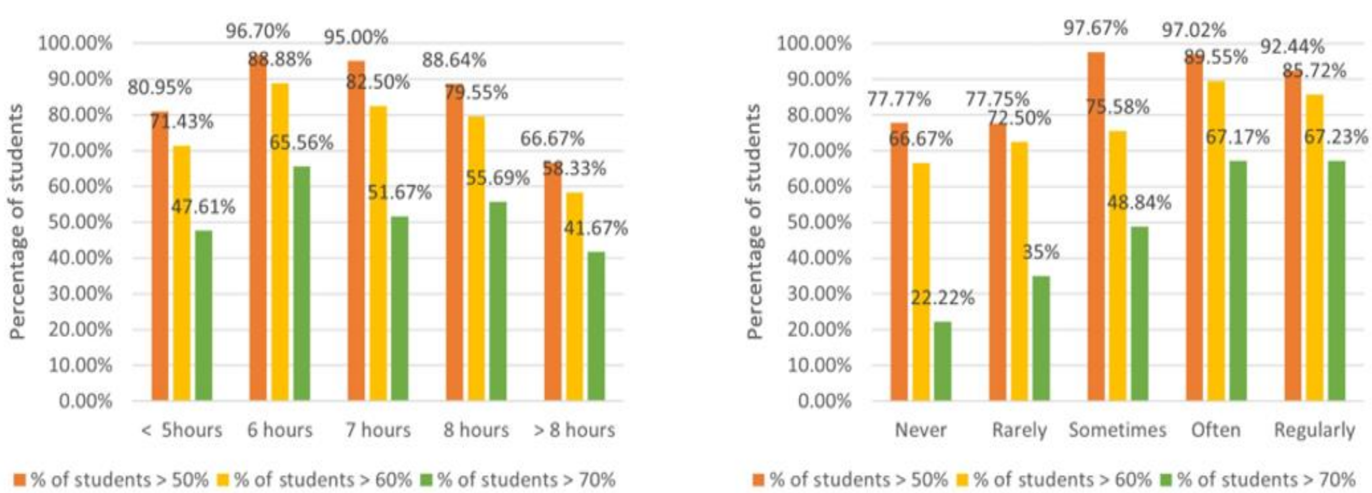
Table 6. Results of the impact of the medium of study.

Parameters	Sub classification	Sample	Mean	Standard deviation	Method used	T value	P value	Hypothesis
Medium of study	Kannada	152	69.01	15.29	T-test	-3.2	0.002	Accepted
	English	178	74.16	13.97				

H_3: Learners' performance is related to how long they sleep.

This study's null hypothesis (Ho) proposes no significant link between the amount of sleep learners get and their academic achievements. The alternative hypothesis (Ha) suggests a meaningful relationship exists. The data indicates that students averaging 6-7 hours of sleep tend to have the highest academic scores, surpassing various performance thresholds more frequently than their peers with shorter or longer sleep durations (see Figure 3a). This trend is further evidenced by the higher average scores within the '6-7 hours' sleep group as depicted in Figure 4a.

Despite these observations, a one-way ANOVA test conducted on this data found no statistically significant differences in academic performance across different sleep duration categories as outlined in Table 7. The resulting p-value of 0.23 which is above the conventional threshold of 0.05 suggests that the duration of sleep does not significantly influence the academic performance of learners.



(a) Duration of sleep (b) Frequency of login

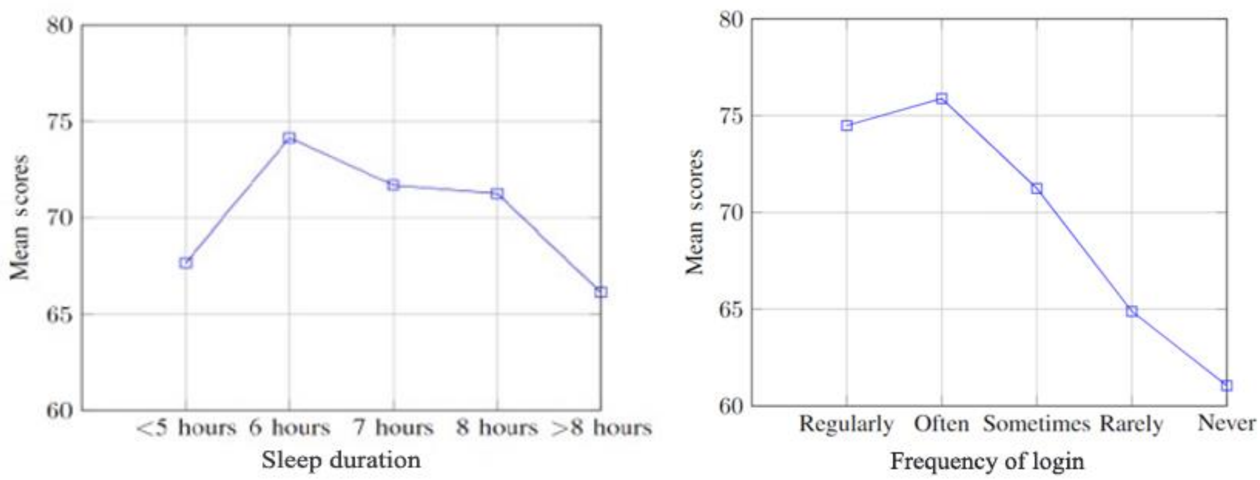
Figure 3. Influence of sleep duration and login frequency on academic achievement.

Table 7. Results of the impact of sleep duration.

Parameters	Sub classification	Sample	Mean	Standard deviation	Method used	F value	P value	Hypothesis
Sleep duration	Less than 5 hours	21	67.67	19.52	ANOVA	1.42	0.23	Rejected
	6 hours	90	74.14	11.19				
	7 hours	120	71.68	12.97				
	8 hours	88	71.24	17.72				
	Greater than 8 hours	11	66.14	21.74				

H_4: Regular login will increase the chances of learners' performance and success rate.

In this study, H_0 hypothesizes the absence of a significant link between the regularity of LMS usage and student academic success. On the other hand, H_1 posits the existence of such a link. Data visualized in Figure 3b indicates that students logging into the LMS "regularly" achieved the highest rates of scores over 70% at 67.23% with the "often " group at a comparable 67.17%. In stark contrast, only 22.22% of the "never " group reached similar performance levels. This descending pattern in performance correlating with decreased LMS usage frequency is further depicted in Figure 4b. Employing a one-way ANOVA to determine the statistical significance, the study revealed that login frequency has a pronounced effect on student results with a p-value of 0.0 as shown in Table 8. These findings emphasize the positive influence of promoting regular and frequent engagement with online courses on learner performance.



(a) Mean score versus duration of sleep (b) Mean score versus frequency of login

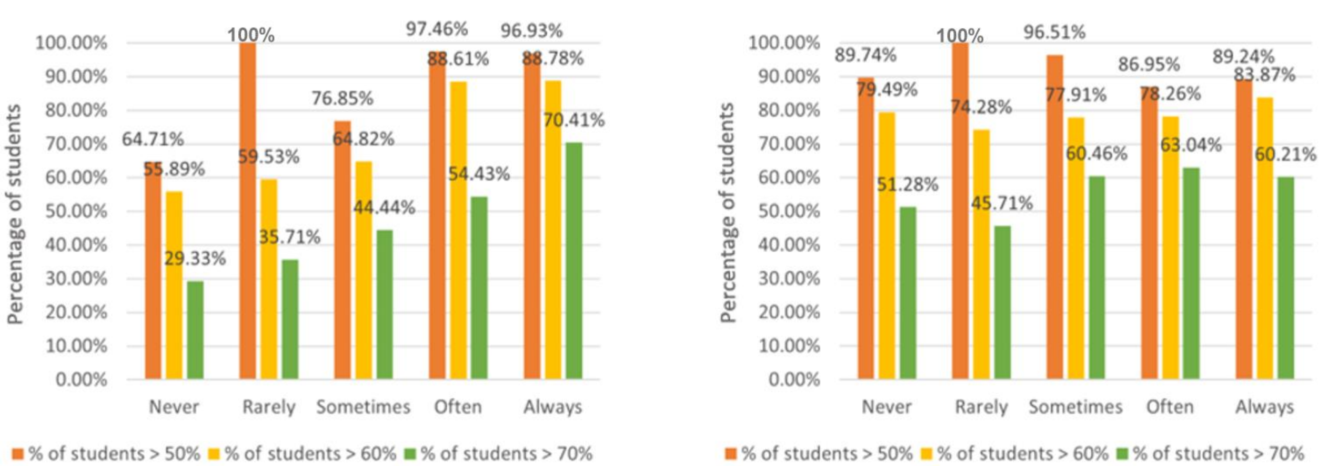
Figure 4. Mean score of duration of sleep and frequency of login.

Table 8. Results of the impact of frequency of login.

Parameters	Sub classification	Sample	Mean	Standard deviation	Method used	F value	P value	Hypothesis
Frequency of login	Regularly	119	74.49	13.53	ANOVA	9.1	0.0	Accepted
	Often	67	75.89	11.73				
	Sometimes	86	71.24	11.43				
	Rarely	40	62.886	22.83				
	Never	18	61.05	12.44				

H_5: Forum interaction has a positive effect on the academic outcome of a learner.

The null hypothesis (Ho) proposes that there is no substantial disparity in educational outcomes between participants who actively engage in forums and those with limited or no participation. On the other hand, the alternative hypothesis (Ha) posits that such a significant difference does exist. A discernible pattern emerges wherein the percentage of students achieving higher scores increases as the level of participation in forums escalates from "never" to "always" (see Figure 5a).



(a) Interactions in forums (b) Viewing online videos

Figure 5. Impact of forum interaction and online lectures viewing on academic performance.

The highest percentage of students achieving scores above 70% is observed among those who consistently engage in discussion forums while the lowest percentage is evident among those who never participate in such forums. Similarly, the mean score for students who frequently login as depicted in Figure 6a surpasses that of their rarely active counterparts. A one-way ANOVA was conducted to rigorously assess the significance of mean score variances among participants with varying levels of forum interaction. The statistical analysis resulted in a p-value of 0.0 as recorded in Table 9 signifying an exceedingly significant difference and corroborating the acceptance of the hypothesis. These findings underscore the potential of promoting and facilitating active engagement in online discussion forums as a means to enhance learner performance through collaborative learning, knowledge exchange and critical thinking.

Table 9. Results of the impact of forum interaction.

Parameters	Sub classification	Sample	Mean	Standard deviation	Method used	F value	P value	Hypothesis
Forum interaction	Always	98	76.14	11.91	ANOVA	10.6	0.0	Accepted
	Often	78	75.88	12.59				
	Sometimes	91	69.58	15.57				
	Rarely	36	62.32	18.96				
	Never	27	64.27	11.22				

H_6: Learners experienced improved academic achievements by spending extra time on online lectures.

The investigation's null hypothesis (H0) posits the absence of notable disparities in the academic achievements of students with different durations of engagement with online lectures. In contrast, the alternative hypothesis (H1) contends that such disparities do exist. The data showed a direct relationship between how long students watched lectures online and the percentage of students scoring above the 50%, 60% and 70% thresholds. The highest success rates were among those categorized as watching lectures "often" or "always " as shown in Figure 5b. Furthermore, Figure 6b shows that the average score for students who consistently engaged with online content (always) was 74.49 surpassing that of students who did not engage (never). An ANOVA test confirmed a significant difference in the mean scores across the five surveyed groups (p = 0.006) as demonstrated in Table 10. The evidence suggests that greater engagement with online lectures correlates with improved academic performance leading to the recommendation that students should be motivated to increase the time they spend on online lectures to potentially enhance their educational results.

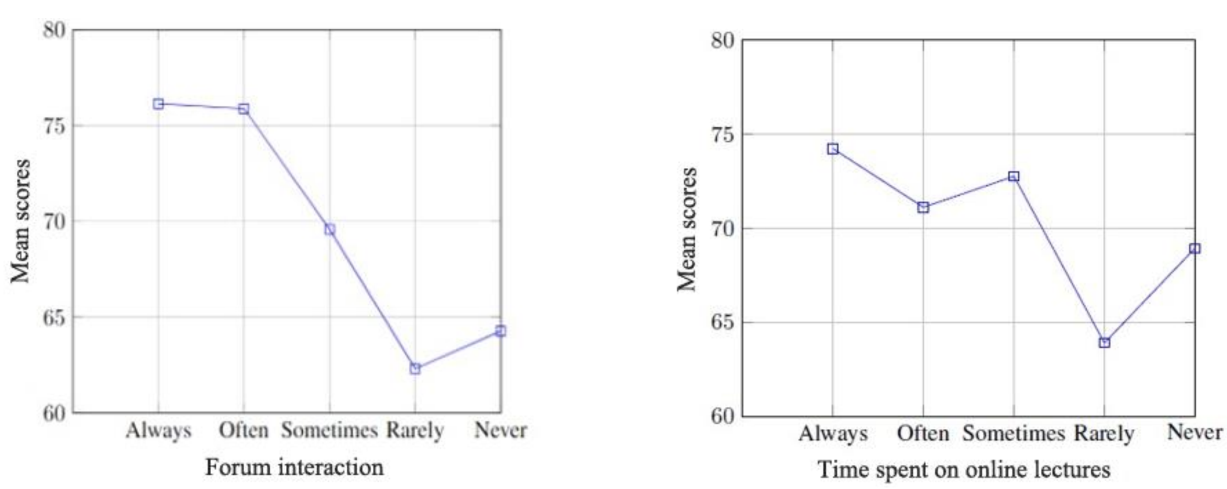


Figure 6. Mean score.

Table 10. Results of the impact of time spent on online lectures.

Parameters	Sub classification	Sample	Mean	Standard deviation	Method used	F value	P value	Hypothesis
Time spent on online lectures	Always	105	74.24	12.16	ANOVA	3.62	0.006	Accepted
	Often	51	71.12	13.26				
	Sometimes	116	72.77	15.31				
	Rarely	34	63.90	19.03				
	Never	24	68.94	16.04				

7. Conclusion and Future Scope

This paper investigates factors influencing academic performance in online learning environments for technical students. Teachers and institutions should focus on fostering engagement, interaction and student support to mitigate barriers and enhance academic outcomes in online learning environments. The findings highlight the necessity of considering contextual parameters such as geographical area and medium of study when designing online learning systems. Adapting online resources to suit different contexts can help close performance disparities. Encouraging frequent login, active participation in forums and allocating sufficient time for learning activities can contribute to improved learner performance. Active participation not only enriches comprehension but also encourages a sense of community, a driving force behind enhanced academic performance. Our study suggests that sleep is undoubtedly crucial for well-being; it may not be the primary factor influencing academic outcomes in this particular context.

Future work can focus on tailored interventions, comparative studies, exploring learning analytics techniques, feature importance analysis and longitudinal studies. Development and implementation of an intervention system to address the challenges identified in this study and improve student outcomes on virtual learning platforms. Carry out comparative research across various fields and educational stages to investigate factors that are specific to the discipline or the context and that may affect learners' performance differently. Explore advanced learning analytics techniques such as predictive modelling, clustering or sentiment analysis to further understand and predict student performance in online education. Conduct longitudinal studies to examine how influential factors evolve over time and their long-term impact on student performance in online learning environments.

8. Implications and Future Limitations

8.1. Implications

The findings of this study hold several noteworthy implications for the field of BL and education as a whole. Teachers, administrators and policymakers may all benefit from in-depth awareness of the variables influencing students' success. Teachers and educational institutions can use the research's insights to create and execute BL programmes that are specifically tailored to the needs and backgrounds of their students. Factors such as geographical location and the medium of study can inform the tailoring of content and support mechanisms to enhance learning outcomes. Amplified student engagement recognizing the importance of factors like login frequency, active forum participation and the time allocated to watching online lectures underscores the significance of interactive and engaging online learning materials. Teachers can use these findings to create more dynamic and interactive e-learning content that fosters higher student engagement. Policymakers can use the knowledge gained from this study to shape and support education policies that promote the effective utilization of BL. This may encompass initiatives related to funding, infrastructure development and teacher training to facilitate the adoption of BL practices. Educational institutions can provide tailored support to students based on their backgrounds and individual needs. For instance, students from different geographical areas may benefit from specific types of support to excel in blended learning environments.

8.2. Future Limitations

This study delivers valuable insights. It is essential to acknowledge its limitations. This study was geographically confined to Karnataka State. Replicating this research in different regions or countries would reveal regional disparities in the influence of these factors on BL. Educational technology and BL environments are in a state of continuous evolution. Future research should explore how emerging technologies and shifts in digital learning environments affect the parameters influencing student performance.

References

Abuhassna, H., Al-Rahmi, W. M., Yahya, N., Zakaria, M. A. Z. M., Kosnin, A. B. M., & Darwish, M. (2020). Development of a new model on utilizing online learning platforms to improve students' academic achievements and satisfaction. *International Journal of Educational Technology in Higher Education, 17*, 1-23. https://doi.org/10.1186/s41239-020-00216-z

Ahuja, S., Kaur, P., & Panda, S. (2019). Identification of influencing factors for enhancing online learning usage model: Evidence from an Indian University. *International Journal of Education and Management Engineering, 9*(2), 15-24. https://doi.org/10.5815/ijeme.2019.02.02

Arbaugh, J. B. (2002). Managing the on-line classroom: A study of technological and behavioral characteristics of web-based MBA courses. *The Journal of High Technology Management Research, 13*(2), 203-223.

Bernard, R. M., Abrami, P. C., Lou, Y., Borokhovski, E., Wade, A., Wozney, L., . . . Huang, B. (2004). How does distance education compare with classroom instruction? A meta-analysis of the empirical literature. *Review of Educational Research, 74*(3), 379-439.

Dewald, J. F., Meijer, A. M., Oort, F. J., Kerkhof, G. A., & Bögels, S. M. (2010). The influence of sleep quality, sleep duration and sleepiness on school performance in children and adolescents: A meta-analytic review. *Sleep Medicine Reviews, 14*(3), 179-189. https://doi.org/10.1016/j.smrv.2009.10.004

Diekelmann, S., & Born, J. (2010). The memory function of sleep. *Nature Reviews Neuroscience, 11*(2), 114-126.

Dubey, S., Piroska, B., & Gautam, M. (2019). Exploration of factors affecting learners' motivation in e-learning. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 5*(2), 2456. https://doi.org/10.32628/cseit1952307

Garrison, D. R., Anderson, T., & Archer, W. (2001). Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of Distance Education, 15*(1), 7-23. https://doi.org/10.1080/08923640109527071

Gruber, R., Wiebe, S. T., Wells, S. A., Cassoff, J., & Monson, E. (2010). Sleep and academic success: Mechanisms, empirical evidence, and interventional strategies. *Adolescent Medicine: State of the Art Reviews, 21*(3), 522-541, x.

Harasim, L. M. (1995). *Learning networks: A field guide to teaching and learning online*. Cambridge, MA: MIT Press.

Hirshkowitz, M., Whiton, K., Albert, S. M., Alessi, C., Bruni, O., DonCarlos, L., & Hillard, P. J. A. (2015). National sleep foundation's sleep time duration recommendations: Methodology and results summary. *Sleep Health, 1*(1), 40-43. https://doi.org/10.1016/j.sleh.2014.12.010

Horn, M. B., & Staker, H. (2011). The rise of K-12 blended learning. *Innosight Institute, 5*(1), 1-17.

Jovanovic, J., Gasevic, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom. *Internet and Higher Education, 33*, 74-85. https://doi.org/10.1016/j.iheduc.2017.02.001

Kaur, P., Kumar, H., & Kaushal, S. (2021). Affective state and learning environment based analysis of students' performance in online assessment. *International Journal of Cognitive Computing in Engineering 2*, 12-20. https://doi.org/10.1016/j.ijcce.2020.12.003

Kintu, M. J., Zhu, C., & Kagambe, E. (2017). Blended learning effectiveness: The relationship between student characteristics, design features and outcomes. *International Journal of Educational Technology in Higher Education, 14*(1), 1-20. https://doi.org/10.1186/s41239-017-0043-4

Lee, J.-E., & Recker, M. (2021). The effects of instructors' use of online discussions strategies on student participation and performance in university online introductory mathematics courses. *Computers & Education, 162*, 104084. https://doi.org/10.1016/j.compedu.2020.104084

Li, J., & Xue, E. (2023). Dynamic interaction between student learning behaviour and learning environment: Meta-analysis of student engagement and its influencing factors. *Behavioral Sciences, 13*(1), 1-15. https://doi.org/10.3390/bs13010059

Moore, M. G. (1993). Theory of transactional distance. *Theoretical Principles of Distance Education, 1*, 22-38.

Moore, M. G., & Kearsley, G. (2011). Distance education: A systems view of online learning. *Cengage Learning.*

Moreno-Marcos, P. M., Muñoz-Merino, P. J., Alario-Hoyos, C., Estévez-Ayres, I., & Delgado Kloos, C. (2018). Analysing the predictive power for anticipating assignment grades in a massive open online course. *Behaviour & Information Technology, 37*(10-11), 1021-1036. https://doi.org/10.1080/0144929x.2018.1458904

Moreno-Marcos, P. M., Pong, T. C., Muñoz-Merino, P. J., & Kloos, C. D. (2020). Analysis of the factors influencing learners' performance prediction with learning analytics. *IEEE Access, 8*, 5264-5282. https://doi.org/10.1109/access.2019.2963503

Panizzon, D. (2015). Impact of geographical location on student achievement: Unpacking the complexity of diversity. In: Bishop, A., Tan, H., Barkatsas, T. (eds) Diversity in Mathematics Education. Mathematics Education Library. In (pp. 41-61). Cham: Springer. https://doi.org/10.1007/978-3-319-05978-5_3.

Picciano, A. G. (2002). Beyond student perceptions: Issues of interaction, presence, and performance in an online course. *Journal of Asynchronous Learning Networks*, *6*(1), 21-40.

Rafi, M., JianMing, Z., & Ahmad, K. (2019). Technology integration for students' information and digital literacy education in academic libraries. *Information Discovery and Delivery*, *47*(4), 203-217. https://doi.org/10.1108/idd-07-2019-0049

Rovai, A. P. (2002). Building sense of community at a distance. *International Review of Research in Open and Distributed Learning*, *3*(1), 1-16. https://doi.org/10.19173/irrodl.v3i1.79

Shea, P., Li, C. S., Swan, K., & Pickett, A. (2005). Developing learning community in online asynchronous college courses: The role of teaching presence. *Journal of Asynchronous Learning Networks*, *9*(4), 59-82.

Sweller, J., Ayres, P. L., Kalyuga, S., & Chandler, P. (2003). The expertise reversal effect. *Educational Psychologist*, *38*(1), 23-31.

Taghizadeh, M., & Hajhosseini, F. (2021). Investigating a blended learning environment: Contribution of attitude, interaction, and quality of teaching to satisfaction of graduate students of TEFL. *The Asia-Pacific Education Researcher*, *30*, 459-469. https://doi.org/10.1007/s40299-020-00531-z

Wei, Y., Shi, Y., MacLeod, J., & Yang, H. H. (2022). Exploring the factors that influence college students' academic self-efficacy in blended learning: A study from the personal, interpersonal, and environmental perspectives. *SAGE Open*, *12*(2), 21582440221104815. https://doi.org/10.1177/21582440221104815

Zhao, L., Chen, K., Song, J., Zhu, X., Sun, J., Caulfield, B., & Mac Namee, B. (2020). Academic performance prediction based on multisource, multifeature behavioral data. *IEEE Access*, *9*, 5453-5465.