International Journal of Computer Techniques–IJCT Volume 13 Issue 1, January - 2026

Open Access and Peer Review Journal ISSN 2394-2231 https://ijctjournal.org/

RESEARCH ARTICLE OPEN ACCESS

# Modeling the Impact of Engagement Parameters on Student Performance in Blended Learning by using Machine Learning

Kuldeep Chauhan [1], Varun Bansal [2], Anil Kumar [3], Vishal Kumar [4]

[1](Computer Science Engineering, Shobhit University, Gangoh, Saharanpur, India
Email: kuldeep.chauhan@shobhituniversity.ac.in)

[2] (Computer Science Engineering, Shobhit University, Gangoh, Saharanpur, India
Email : Varun.bansal@shobhituniversity.ac.in )

[3](Computer Science Engineering, Galgotias College of Engineering and Technology, Greater Noida, India
Email : vats.anilkumar@gmail.com)

[4] (Computer Science Engineering, Shobhit University, Gangoh, Saharanpur, India
Email : Vishal.kumar@shobhituniversity.ac.in )

----------------------------------------************************----------------------------------

## Abstract:

The expeditious growth of blended learning has created a demand for analytical methods that can quantify how digital engagement affects educational outcomes across various academic programs. This study will reveal a cross-course evaluation that combine supervised machine learning, engagement Modeling and comparative performance analysis to better understand the pupil's behaviour within blended and traditional instructional conditions. By using the dataset partitions representing four academic programs- B.Tech 2nd year, B.Tech 3rd year, B.Sc 3rd year and BCA 3rd year-the study examines the relationship between structured engagement in blended learned subjects and resulting academic performance. The analysis comprise performance averages, engagement-to-performance correlations, and model-driven predictions created through ML algorithms such as Linear Regression, Decision Trees, Random Forests, and Support Vector Regression. Findings show variations in blended learning effectiveness across these courses, with engagement demonstrating powerful predictive value in computer engineering programs and modest or inconsistent alliance in other disciplines. The recent work emphasizing learner analytics and AI-supported evaluation setup in higher education. The study highlights how engagement parameters and algorithmic modeling can support an extensive understanding of blended learning dynamics, offering evidence-based understanding for instructional design, policy decisions, and future adaptive learning research.

***Keywords*** *— Machine Learning, Model Prediction, Blended Learning, Parameter Influence, Performance Analysis.*

----------------------------------------************************----------------------------------

## I. INTRODUCTION

Over the last decade the shift toward blended learning environments has expanded significantly, with institutions increasingly integrating online components into conventional classroom arrangements. This shift, inspired by technological advances and evolving pedagogical expectations. As educational setups incorporate digital learning tools, researchers have focused on understanding how students interact with this digital equipment are central to improving curriculum design, engagement strategies, etc. [1]. Blended learning, presents a unique way where both in-person and online interactions contribute to academic excellence, making it prompt to analyse the interchange between engagement behaviours and performance outcomes [2].

The dissemination of digital traces-such as video engagement metrics, navigation patterns, and viewing time of digital contents-has allowed the use of analytic and computational techniques that were previously unavailable in traditional classroom setup. Recent studies highlight the value of integrating artificial intelligence (AI) and machine learning (ML) techniques to inspect learning processes, predict student performance, and identify meaningful engagement patterns [3]. As every academic program is differ in its curriculum complications, student background and prior knowledge, and digital readiness, cross-course comparative analysis has come up as an important direction for evaluating how blended learning functions across several situations.

Although blended learning continues to grow increasingly common, relatively few studies examine how engagement functions as a parameter within different academic disciplines simultaneously [4]. This lack of multi-course comparative evidence limits educators' ability to extend results or grasp how different student groups benefit from blended learning. While ML-based models have been rapidly used to forecast performance and detect at-risk learners, there is limited empirical research showing how these models act when engagement parameters are simplified, or used continuously across diverse course structures. Prior research has shown that performance prediction models gain substantial accuracy when engagement factors are meaningfully merged, but these effects change based depending on the instructional design and learners' digital competencies [5].

The present study examines these gaps by conducting a multi-course evaluation of blended learning performance using student datasets from four different academic programs: B.Tech 2nd year, B.Tech 3rd year, B.Sc 3rd year, and BCA 3rd year. The analysis comprises engagement measures, performance metrics, correlation assessments, and supervised ML models to discover exact differences across programs. The major aim is to provide an evidence-driven understanding of how engagement interconnect with academic outcomes in blended learning environment and to extend the power of algorithmic prediction models in defining these patterns. By investigating blended and traditional learned subjects simultaneously, the present study contributes a holistic viewpoint on student learning behaviors and performance steadiness, building on ongoing efforts to combine computational approaches into higher educational research.

## II. LITERATURE REVIEW

The merging of blended learning within higher education has been increasingly explored as universities turn toward hybrid instructional approaches. Researchers have marked that the combination of face-to-face instruction with digital learning tools allows flexibility, promotes self-paced learning, and enhances access to course contents, especially in technical and multidisciplinary programs [6]. These blended formats have been shown to impact not only academic achievement but also students' motivation and long-term engagement with course materials.

Recent studies shows that digital engagement-measured through video interactions, time-on-task, and navigation behaviours these all serves as a major predictor of learning outcomes. Studies conducted in the last few years have highlight that blended learning becomes increasingly growing, engagement analytics must evolve to find varied learning behaviours throughout courses and cohorts [7]. Researchers have also suggested that engagement metrics can serve as early indicators of academic challenges, enabling instructors to step in actively.

Machine learning has also gained significant focus as a methodological approach for studying learning behaviour and performance. Several works reveals that predictive algorithms, including regression-based models, decision trees, and neural networks, can effectively find academic patterns and forecast student outcomes when associated with structured engagement data [8]. These models improve interpretability by quantifying how individual parameters-like course attendance, content interactions, and digital awareness-put up to performance variation.

Comparative studies across academic courses are comparatively very fewer. Existing literature often focuses on single-course or single-semester analyses. Which limits the understanding of how blended learning functions in heterogeneous institutional environments [9]. Furthermore, the variability of digital readiness, subject toughness, and instructional model across academic levels suggests that uncovering from one program cannot be universally generalized. Scholars have proclaimed that cross-program analyses using continuous engagement frameworks are critical to measure the robustness of blended learning models [10].

Broadly, existing research points toward three major research gaps that this study aims to address:

1. Limited cross-course relative evidence on blended learning performance;
2. Under-examined engagement-to-performance relationships in multi-course datasets
3. Insufficient use of combining machine learning frameworks across heterogeneous academic programs.

The present study extends the current literature by applying a continuous engagement metric, standardized performance measurement, and supervised ML models across four different programs. This approach generates insights into how blended learning effectiveness varies by academic context and how engagement feature works with traditional performance measures across distinct programs.

## III. Methodology and Experimental Study

### 3.1 Research Design

This study followed a quantitative, multi-course analytical design that examined how engagement feature with blended learning content relates to academic performance across four undergraduate programs. The design was constructed to support cross-program comparability. This ensures that the same analytical framework was applied to each program. This integration with recommendations in ultra-modern learning analytics research that focus consistency in modelling a heterogeneous academic contexts based datasets [11]. The methodology comprises dataset preparation, engagement parameter construction, performance measuring, correlation analysis, and supervised machine learning evaluation.

### 3.2 Dataset Structure and Preparation

The dataset was prepared in four separate worksheet files, each represent a distinct academic program: B.Tech 2nd year, B.Tech 3rd year, B.Sc 3rd year, and BCA 3rd year. Each worksheet contained student names and their marks in the subjects taught within that specific program. The study did not merge worksheets because each program has a different set of subjects and a different blended learning component. Treating each sheet independently ensured that subject-specific and course-level variations remained complete, maintaining methodological clarity.

Let S_i denote the set of subject scores for student i in a given program. In notation:

$$S\_i = \{ s\_i1,s\_i2,...,s\_i(n\_i) \}$$

All marks were normalized by converting missing values to zero, a preprocessing step frequently followed in educational analytics to avoid inconsistencies arising from incomplete reporting [12].

### 3.3 Construction of Engagement Parameter

Though direct digital interaction logs were not available for the blended subjects to use thoroughly. Based on course curriculum documentation, students studying Computer Graphics (CG) were assigned an estimated two hours of blended learning engagement per week, whereas students studying Internet and Web Technology (IWT) were assigned one hour per week. Traditional subjects, managed entirely through face-to-face instruction, were assigned an engagement value of zero. This method follows the principle of using heuristic-based engagement indicators when explicit digital traces are absent [13].

E_i = {2 if student i enrolled in CG; 1 if enrolled in IWT; 0 otherwise}

### 3.4 Performance Computation

Academic performance was separated into two primary measures: blended and traditional performance. Blended performance was calculated by averaging the marks obtained in the blended subject of each course. Additionally, traditional performance showed the average score across all non-blended subjects within the same program.

***Blended average:***

$$BlendedAvg\_i = (1 / |B\_i|) * \Sigma \ (b \in B\_i) \ b$$

***Traditional average:***

TraditionalAvg_i = (1 / |T_i|) * Σ (t ∈ T_i) t

This two-fold structure enabled the study to differentiate instructional mode effects from subject-specific difficulty or assessment variance. Such a deviation is consistent with the analytical approaches used in comparative measures of instructional formats in higher education [14].

### *3.5 Analytical Variables for Cross-Course Comparison*

To support systematic comparison among all the four programs, four analytical variables were derived. The first captured the correlation between engagement and blended performance which indicating how strongly digital involvement related to achievement. The second variable measured the correlation between blended and traditional performance which revealing the performance consistency across different instructional methods. The third variable measured the performance gain or decline in blended learning using percentage divergence from traditional averages. The fourth variable represented the highest coefficient of determination ($R^2$) attained by any used machine learning model.

***Performance gain (%):***

Gain(%)_i = [(BlendedAvg_i - TraditionalAvg_i) / TraditionalAvg_i] × 100

***R squared (R^2):***

$R^2 = 1 - [\, \Sigma (y_i - \hat{y}_i)^2 / \Sigma (y_i - \bar{y})^2 \,]$

These indicators provided unite analytical structure capable of point up cross-program similarities and differences [15].

### *3.6 Machine Learning Evaluation*

Four supervised ML algorithms-Linear Regression, Decision Tree Regression, Random Forest Regression, and Support Vector Regression-were used to estimate the predictive power of the engagement parameter. In each model, engagement hours set out as the predictor variable and blended performance set out as the target variable.

***Practical accuracy P(±2):***

P(±2)= (# of predictions with |y_i-y_hat_i| <=2/n) * 100

The dataset for each program was divided into training (75%) and testing (25%) subsets. Model performance was measured using the coefficient of determination, mean absolute error and a practical accuracy measure showing the percentage of predictions come within a two-mark range of the actual score. The modelling approach show commonly used strategies in predictive learning analytics, where simplicity, interpretability, and generalization capacity are ranked [16].

### *3.7 Visualization Framework*

A set of visualizations was prepared to consolidate the analytical results in a manner that reveals intuitive interpretation. These included performance comparison graphs, performance gain line plots, correlation heatmaps, scatter diagrams and model accuracy comparisons. These visual set out to reinforce numerical findings and highlight key cross-course patterns. The use of visual analytics balanced with suggestions emphasizing the value of graphical interpretation in complex learning datasets [17].

## IV. RESULTS AND FINDINGS

This section give out the analytical findings procure from the statistical evaluation, feature-value ranking, and ML model performance.

### *4.1 Overview of Analytical Outputs*

The results derived from the processed datasets shows clear patterns that differentiate blended learning outcomes across the selected four academic programs. After evaluating blended and traditional performance averages, engagement parameters, performance gain percentages, correlation values, and model accuracy metrics, the findings reveal that the influence of blended learning varies significantly across cohorts Fig. 1.

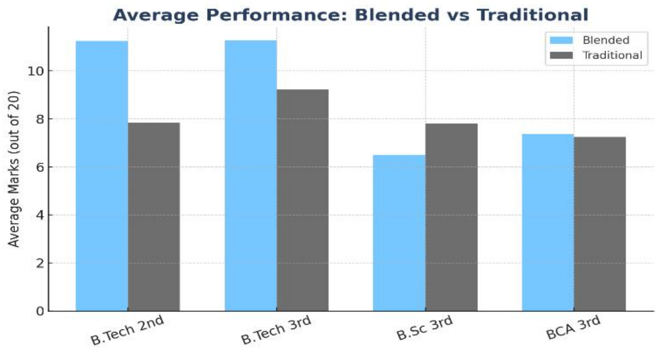


Fig. 1: Average Performance of Blended vs. Traditional Learning Subjects

These differences show that the achievement of blended learning differs and is affected by a number of factors, including academic discipline, course structure, learner preparedness, and engagement capability. These results' interpretation corresponds with recent studies on comparative blended learning, which underscores the significance of context-specific evaluation [18].

### *4.2 Performance Comparison across Instructional Modes*

A clear distinction came out between blended and traditional performance within each program. The B.Tech 2nd and 3rd year programs showed significantly better performance in blended learned subjects with their blended averages significantly higher their traditional averages.

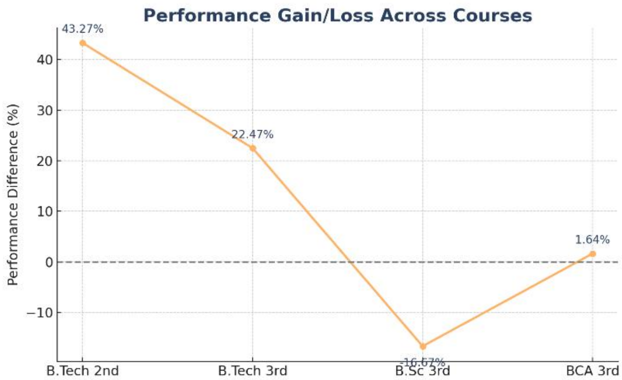


Fig. 2: Performance across courses

These positive variances indicated that the blended learning elements in these courses might have delivered more time for learning, conceptual clarity, or additional digital scaffolding to aid pupils succeed. The B.Sc 3rd year cohort showed comparatively less accomplishment in the blended subject than in traditional subjects. This result shows that the blended instructional approach may not have aligned optimally with the student's prior or cognitive expectations. The BCA 3rd year cohort express nearly identical blended and traditional averages, indicating neutral effect. The distributional trends discovered by the performance comparison visualization reinforce these program-specific shift.

### *4.3 Engagement-Performance Relationships*

Correlation analysis reveals solid variability in how engagement influenced blended performance across programs. The strongest engagement-to-performance correlation emerged in the B.Sc 3rd year cohort, despite the cohort showing less overall blended performance. This suggests that although pupils in this group acted modestly, their performance was still highly tied to the engagement parameter. The B.Tech 3rd year cohort showed with an equally strong correlation, reflecting effective distribution between the instructional approach and student engagement behavior. In contrast, the B.Tech 2nd and BCA 3rd year programs showed relatively strong correlations, showing that engagement contributed positively.

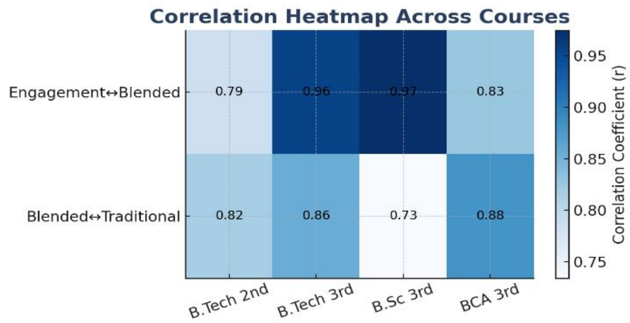


Fig. 3: Correlation across courses

The correlation between blended and traditional performance show up another important dimension: performance consistency over instructional modes. Here, the BCA 3rd year cohort showed the highest alliance, implying that learners who performed well traditionally pretend to continue that performance in blended settings. While, the B.Sc 3rd year cohort showed the weakest cross-mode correlation which indicate forking between blended and traditional learning paths. These observed variations echo insights from studies presenting that blended learning doesn't uniformly help all learners and may generate different performance patterns across disciplines.

### *4.4 Performance Gain Analysis*

The performance gain standard provided a quantitative measure of whether blended learning put up with positively or negatively to achievement relative to traditional subjects. The B.Tech 2nd year cohort reveal the highest gain, exceeding 40%, followed by a remarkable positive gain in the B.Tech 3rd year cohort. Such gains propose strong structure between blended instructional design and student learning in engineering courses.


Fig. 4 Blended vs Traditional Performance Course wise

The BCA 3rd year cohort showed marginal gain, designate balanced performance across modes with neither positive nor disadvantage in blended direction. The B.Sc 3rd year cohort demonstrated negative gain, revealing that the blended component may not have enough supported learners relative to traditional instruction. Negative gains of this type have been accredit in earlier research to cognitive overburden, poor digital readiness, or disarrange between content complexity and the digital learning procedure.

### *4.5 Predictive Modelling Outcomes*

The machine learning models showed varying levels of predictive accuracy depending on the cohort. For the B.Tech 3rd and B.Sc 3rd year sections, the supervised models achieved higher predictive strength, with the Random Forest and Linear Regression models generating $R^2$ values above 90%. This guides that engagement hours set out as a reliable predictor for blended performance in these programs.

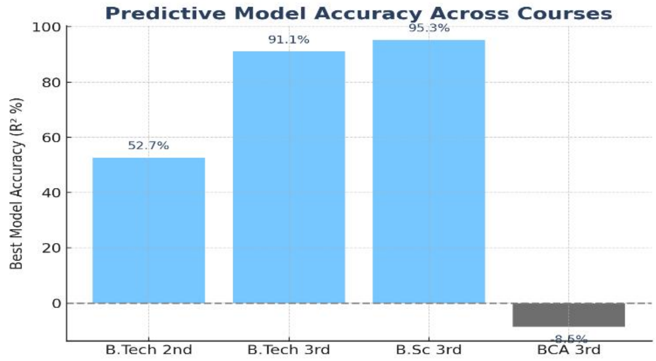


Fig. 5: Average Performance

Conversely, the B.Tech 2nd year course showed moderate predictive accuracy, while the BCA models showed negative $R^2$ values, indicating negative generalization. The negative $R^2$ for the BCA cohort can be attributed to the less change in engagement across students and the near-equality within blended and traditional performance averages. This reduces the model's ability to quantify meaningful predictive patterns. The comparative model accuracy visualization well captured these program-level variances, supporting observations made in predictive learning analytics studies.

### *4.6 Consolidated Interpretation*

When combined the results showed that blended learning doesn't employ a uniform impact across academic programs. Strong gains and correlations in the engineering cohorts contrast with the limited or negative impact noticed in the science and computing cohorts. Predictive models thrive where engagement variability and instructional alignment were high, and underperformed where engagement patterns were constant or where the blended instructional component didn't sufficiently help learners.

These findings emphasize the importance of tailoring blended learning approaches to the academic and cognitive characteristics of different programs. They further spotlight the value of using analytic and predictive approaches to identify where blended modes require improvement.

## V. Conclusion and Discussion

The findings of this study highlight the complex and program-dependent nature of blended learning effectiveness within higher education environments. By analysing four distinct academic cohorts-spanning engineering, computer applications, and science-clear differences emerged in how students responded to the blended instructional mode. These differences reflect not only variation in student preparedness and subject complexity but also the structural alignment between digital learning components and learners' academic trajectories. Similar patterns have been noted in other cross-disciplinary evaluations, where blended learning demonstrated uneven performance benefits across domains.

The engineering cohorts (B.Tech 2nd and 3rd year) demonstrated the most favourable response to blended instruction. These programs exhibited both strong blended performance and high positive performance gains relative to traditional subjects. The correlation analysis reinforced these outcomes, particularly in the B.Tech 3rd year group, where engagement was strongly associated with improved blended performance. This finding suggests that when digital components are embedded in conceptually structured courses that require visualisation, modelling, or iterative exploration, students may benefit substantially from the additional digital exposure. The predictive modelling results further supported this interpretation, with high $R^2$ values indicating that engagement was a reliable predictor of blended performance in these groups. These outcomes align with recent work that demonstrates the importance of alignment between digital task design and subject-specific cognitive requirements.

In contrast, the B.Sc 3rd year cohort presented a markedly different pattern. Despite exhibiting one of the highest engagement-to-performance correlations, the group underperformed in blended settings relative to their traditional subjects, yielding a negative performance gain. This discrepancy suggests that although engagement was consistent, it did not translate into academic benefit. The divergence between blended and traditional outcomes may signal limitations in the adaptability of the blended content to the students' domain knowledge or learning preferences. Factors such as digital literacy, subject complexity, or cognitive load may have constrained students from maximising the benefits of the blended format-an observation consistent with studies indicating that blended learning can pose challenges when learners are insufficiently prepared for self-regulated digital study.

The BCA 3rd year cohort showed a neutral effect, with nearly identical blended and traditional averages. Models trained on the BCA data performed poorly, as indicated by negative $R^2$ scores. This is likely due to the lack of variance in engagement-every student received the same engagement value-and the closely clustered distribution of performance scores. When both the predictor and outcome variables show minimal dispersion, supervised models have limited capacity to detect meaningful trends. This reinforces the principle that predictive learning analytics are most effective when engagement measures reflect actual behavioural differences, rather than uniform instructional inputs.

Taken together, the cross-cohort results reveal that blended learning effectiveness depends not only on the presence of digital components but also on the degree of meaningful learner engagement, program-specific instructional design, and cognitive alignment. Programs where digital elements complement the disciplinary learning structure tend to benefit more, while programs requiring closer instructor mediation or sequential scaffolding may not exhibit similar advantages. This supports the broader argument that blended learning cannot be designed uniformly across disciplines; its outcomes are inherently shaped by pedagogical context and learner readiness.

The study also demonstrates the utility of integrating computational techniques, such as correlation estimation and supervised machine learning, into the evaluation of blended learning systems. These methods provided deeper insights into the relationships between engagement and performance and revealed the conditions under which predictive modelling yields accurate results. The use of consistently derived engagement heuristics, although not as rich as click-stream data, proved sufficient to reveal meaningful trends across cohorts. This approach may be particularly useful for institutions that implement blended learning but lack fully instrumented digital learning platforms.

However, certain limitations must be acknowledged. First, the engagement parameter was inferred rather than measured directly, which may obscure subtle behavioral variations. Future studies could incorporate real-time analytics from learning management systems to capture more fine-grained engagement indicators. Second, the dataset was limited to offline assessment scores; incorporating continuous assessment, assignment analytics, and competency-based indicators could yield a more comprehensive view of learning progression. Third, the study examined only one blended subject per cohort, which constrains generalisability across varied subject types.

Despite these limitations, the results offer valuable insights for educators and administrators. The findings emphasize the importance of tailoring blended learning to disciplinary needs and underscore the necessity of monitoring engagement patterns to detect where blended formats may require redesign. The demonstrated success of predictive models in certain cohorts also suggests opportunities for early-warning systems, adaptive learning pathways, and targeted academic support.

In conclusion, this study provides a structured analytical evaluation of blended learning effectiveness across four undergraduate programs using engagement metrics, performance comparisons, and predictive modelling. The results confirm that blended learning benefits are not uniform; they depend on program characteristics, learner readiness, and the alignment between digital and traditional instructional elements. By leveraging analytic frameworks, institutions can better understand these dynamics and refine blended learning designs to support diverse learner populations more effectively.

## VI. FUTURE WORK

Future work should focus on incorporating richer engagement data derived directly from digital learning platforms. While this study employed a structured heuristic to estimate weekly engagement hours, the integration of clickstream logs, video interaction analytics, and detailed time-on-task records would enable the construction of more accurate behavioural profiles and more robust predictive models. Beyond engagement measurement, future studies should also expand performance indicators to include formative assessments, assignment analytics, and competency-based evaluations, allowing a more holistic understanding of how blended learning affects different dimensions of student achievement.

Another direction for future research lies in applying more advanced AI methods capable of capturing non-linear and temporal learning patterns. Neural models, sequence-based architectures, and explainable AI systems could offer deeper insight into how engagement evolves over time and how these patterns influence learning outcomes. Expanding the dataset to include additional cohorts or longitudinal observations would further support the development of adaptive blended learning frameworks that can dynamically respond to learner needs and program-specific characteristics.

## ACKNOWLEDGEMENTS:

We are thankful to Shobhit University, Gangoh and Galgotias College of Engineering and Technology for the assistance and all technical support. We assure that the data is collected by self in the Shobhit University and no moderations are made in this. All the data are used in its original form only labelling applied on it.

***Authors Credits:***

**Kuldeep Chauhan:** Structure the analysis & conceived the idea and, wrote -original draft,

**Varun Bansal:** Contemplated the analysis, Visualization, Conceptualization, Methodology, Validation, Investigation, and Supervision,

**Anil Kumar:** Supervision, Writing – review & editing.

**Vishal Kumar:** Visualization, Conceptualization, Writing – review & editing.

## REFERENCES

[1] Asiksoy, G. (2025). Predicting Student Performance in a Blended Learning Course Using Machine Learning. In Smart Infrastructures in the IoT Era (pp. 1251-1263). Cham: Springer Nature Switzerland.

[2] Nguyen, H. T., Pham, L. T., Nguyen, V. A., & Do, K. T. (2025). Early prediction of student performance based on behavioral data in blended

learning. The International Journal of Information and Learning Technology, 42(3), 311-328.

[3] Azizah, Z., Ohyama, T., Zhao, X., Ohkawa, Y., & Mitsuishi, T. (2024). Predicting at-risk students in the early stage of a blended learning course via machine learning using limited data. Computers and Education: Artificial Intelligence, 7, 100261.

[4] T. M. Osaili, L. C. Ismail, H. M. ElMehdi, A. A. Al-Nabulsi, A. O. Taybeh, S. T. Saleh, H. Kassem, H. Alkhalidy, H. I. Ali, A. S. Al Dhaheri, and L. Stojanovska, (Mar. 2023) ''Comparison of students' perceptions of online and hybrid learning modalities during the COVID-19 pandemic: The case of the University of Sharjah,'' PLoS ONE, vol. 18, no. 3, Art. no. e0283513, doi: 10.1371/journal.pone.0283513.

[5] Hamadneh, N. N., Atawneh, S., Khan, W. A., Almejalli, K. A., & Alhomoud, A. (2022). Using Artificial Intelligence to Predict Students' Academic Performance in Blended Learning. Sustainability 2022, 14, 11642.

[6] Ciolacu, M. I., & Svasta, P. (2021, April). Education 4.0: AI empowers smart blended learning process with biofeedback. In 2021 IEEE Global Engineering Education Conference (EDUCON) (pp. 1443-1448). IEEE.

[7] Han, F., & Ellis, R. A. (2021). Predicting students' academic performance by their online learning patterns in a blended course. Educational Technology & Society, 24(1), 191-204.

[8] Evangelista, E. (2021). A hybrid machine learning framework for predicting students' performance in virtual learning environment. International Journal of Emerging Technologies in Learning (iJET), 16(24), 255-272.

[9] Han, F., & Ellis, R. A. (2021). Predicting students' academic performance by their online learning patterns in a blended course. Educational Technology & Society, 24(1), 191-204.

[10] Alraddadi, S., Alseady, S., & Almotiri, S. (2021, March). Prediction of students academic performance utilizing hybrid teaching-learning based feature selection and machine learning models. In 2021 International Conference of Women in Data Science at Taif University (WiDSTaif) (pp. 1-6). IEEE.

[11] Xu, Z., Yuan, H., & Liu, Q. (2020). Student performance prediction based on blended learning. IEEE Transactions on Education, 64(1), 66-73.

[12] Salas-Rueda, R. A. (2020). Perception of students on blended learning considering data science and machine learning. Campus Virtuales, 9(1), 125-135.

[13] Van Goidsenhoven, S., Bogdanova, D., Deeva, G., Broucke, S. V., De Weerdt, J., & Snoeck, M. (2020, March). Predicting student success in a blended learning environment. In Proceedings of the tenth international conference on learning analytics & knowledge (pp. 17-25).

[14] Chango, W., Cerezo, R., & Romero, C. (2019, December). Predicting academic performance of university students from multi-sources data in blended learning. In Proceedings of the second international conference on data science, E-learning and information systems (pp. 1-5).

[15] Raga, R. C., & Raga, J. D. (2019, July). Early prediction of student performance in blended learning courses using deep neural networks. In 2019 International Symposium on Educational Technology (ISET) (pp. 39-43). IEEE.

[16] S. Makridakis, ''The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms,'' Futures, vol. 90, pp. 46–60, Jun. 2017, doi: 10.1016/j.futures.2017.03.006.

[17] Zacharis, N. Z. (2016). Predicting student academic performance in blended learning using artificial neural networks. International Journal of Artificial Intelligence and Applications, 7(5), 17-29.

[18] S. K. Howard, J. Ma, and J. Yang, (Oct 2016) ''Student rules: Exploring patterns of students' computer-efficacy and engagement with digital technologies in learning,'' Comput. Educ., vol. 101, pp. 29–42. doi:10.1016/j.compedu.2016.05.008.