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RESEARCH ARTICLE

Ensemble and Multimodal Approaches for Analyzing Student Engagement and Flexibility in Online Learning: A Review

P. Nagajothi*, M. V. Srinath

Abstract

The rapid growth of online learning environments has intensified the need to understand student engagement in order to enhance learning effectiveness and academic outcomes. Student engagement is typically inferred from digital traces such as login frequency, video viewing behavior, discussion participation, and assessment performance. However, another critical dimension of online learning is student flexibility, encompassing time management, self-regulation, and adaptability to learning schedules has received comparatively limited attention in existing research. This review paper systematically examines recent studies on student engagement analysis, with a particular focus on data modalities, Machine Learning (ML) and Deep Learning (DL) models, ensemble learning techniques, and multimodal learning strategies. The surveyed literature reveals extensive use of traditional ML algorithms and deep neural networks, often relying on single-source data and standalone models. While these approaches demonstrate promising predictive performance, they frequently fail to capture the complex and dynamic nature of student behavior in online settings. Recent trends indicate a growing interest in ensemble learning methods, which integrate multiple models to enhance prediction accuracy, robustness, and generalizability. Despite this progress, the review identifies significant research gaps, including the limited incorporation of flexibility-related features and the absence of comprehensive ensemble-based multimodal frameworks that jointly model engagement and flexibility. Based on the analysis, this paper argues that integrating engagement indicators with flexibility attributes through ensemble and multimodal learning approaches can provide a more holistic and reliable understanding of student behavior. Such frameworks have the potential to support early intervention, personalized learning, and improved decision-making in online education systems.

Keywords: Online Learning, Student Engagement, Flexibility, Machine Learning, Deep Learning, Ensemble Model.

[1]Research Scholar, S.T.E.T. Women's College (Autonomous), (Affiliated to Bharathidasan University, Tiruchirappalli), Sundarakkottai, Mannargudi - 614016, Thiruvarur Dt., Tamil Nadu, India.

[2]Research Supervisor, S.T.E.T. Women's College (Autonomous), (Affiliated to Bharathidasan University, Tiruchirappalli), Sundarakkottai, Mannargudi - 614016, Thiruvarur Dt., Tamil Nadu, India.

***Corresponding Author:** P. Nagajothi, Research Scholar, S.T.E.T. Women's College (Autonomous), (Affiliated to Bharathidasan University, Tiruchirappalli), Sundarakkottai, Mannargudi - 614016, Thiruvarur Dt., Tamil Nadu, India, E-Mail: sujaijothi16@gmail.com

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Introduction

The advancement in computer and network technology that focuses on communication among students and openness of learning resources supports online learning or distance education as the terms, mobile learning, e-learning, distance education, and web-based learning can be used interchangeably (Okronipa, A. Q., et al., 2024; Yilmaz, A. B., & Banyard, P. 2020). Online learning is based on acquiring effective learning and is related to the continuous improvement of students' cognitive levels. In an online learning environment, students should actively join in learning and communicate adequately with their peers and teachers. It is considered that flexibility in learning supports students' persistence when dealing with difficulties. Distance education is regarded as a highly flexible learning approach and it offers freedom in scheduling, location, pace of study, and instructional delivery.

Moreover, the topic of student engagement has been discussed and gained popularity recently as it has been accepted as an important effect on the course and

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student success (Di Biase, A. 2021; Yang, D., *et al.,* 2023; Vijayalakshmi, G., & Srinath, M. V. 2025). It also becomes more vital in the context of distance learning (Di Biase, A. 2021). Although distance education has several advantages and disadvantages, there is a need to explore the quality of distance education to have good learning experiences (Yilmaz, A. B., & Banyard, P. 2020). It is said that engagement in learning is an important issue in understanding the work of online courses (Mustapha, Y., et al, 2023; Vijayalakshmi, G., & Srinath, M. V. 2020) and should be examined (Yilmaz, A. B., & Banyard, P. 2020) along with the issue of flexibility. Therefore, the current study intended to examine within the realm of tertiary distance education, this study explores the potential correlation between instructional adaptability specifically regarding scheduling, pedagogical interaction, and curricular substance and the tripartite dimensions of learner involvement, encompassing affective, cognitive, and active behavioural components.

It is generally recognized that learner involvement comprises three distinct pillars: the active, the intellectual, and the emotional. Specific markers or observable traits define each of these categories. Active involvement entails a student's physical interaction with educational tasks, demonstrated through consistent attendance, diligence, and appropriate classroom behavior. Intellectual involvement concerns the psychological energy dedicated to academic work, evidenced by comprehensive mastery, autonomous oversight of one's habits, and critical thinking. Emotional involvement represents the internal dedication to the educational process, signalled by a feeling of integration and favourable perceptions of instructors, classmates, and the physical or digital campus. A comprehensive directory of these specific metrics is provided (Bond, M., et al., 2020).

Within the domain of digital instruction, the degree to which learners are involved serves as a primary determinant of pedagogical success (Aliyu, J., et al., 2022). This concept represents the depth of enthusiasm, inquisitiveness, and active contribution a scholar demonstrates during their studies. It integrates psychological, physical, and intellectual components, which collectively dictate the manner in which individuals engage with academic materials, fellow students, and their mentors. Furthermore, those who maintain high levels of immersion typically exhibit superior knowledge durability, achieve higher scholastic marks, and cultivate vital competencies like analytical reasoning and logic-based resolution (Li, J., & Xue, E. 2023). Cultivating a sense of involvement within virtual educational environments is especially vital, as these platforms lack the tangible presence, direct interpersonal communication, and spontaneous social signals found in conventional lecture halls. In the absence of such features, scholars frequently experience a sense of alienation or detachment, which often suppresses their drive and academic progress.

Nevertheless, the integration of thoughtfully constructed methodologies including dynamic audio visual tools, instantaneous critiques, group-based assignments, and customized instructional trajectories can markedly bolster learner immersion and alleviate the hurdles typical of remote schooling (Garcia, M. B., & Yousef, A. M. F. 2022; Shively, K., & Sydnor, J. 2023; Yousef, A. M. F., et al., 2023). By encouraging students to participate as active stakeholders in their pedagogical path, digital platforms can establish a more deeply engaging and productive atmosphere. These focus-driven techniques ensure that web-based instruction evolves from a mere alternative into a fundamentally life-changing academic paradigm.

The adaptability inherent in dual-mode or integrated educational settings motivates a higher number of scholars to engage with their courses during instances when personal illness or domestic responsibilities might have otherwise prevented their presence. Furthermore, this approach promotes equity in academic access for marginalized populations and offers a more robust framework for assistance through two distinct communicative channels. Conversely, integrated instruction can intensify the burden on educators, who are tasked with modifying their pedagogical frameworks to suit the specific requirements of this multifaceted arrangement while ensuring academic rigor remains constant (Bülow, M. W. 2022). Because of the structural configuration of these sessions, certain learners may perceive a greater sense of estrangement from both their mentors and their peers; consequently, fostering energetic involvement often poses a significant challenge in such mixed-format settings. Although Bülow, M. W. (2022) review focused on the challenges and opportunities of designing effective hybrid learning environments for the teacher, consequently, scholars engaging across diverse educational settings must modify their approaches to cultivate productive atmospheres for vigorous involvement, catering to the needs of both physically present and distant participants.

Global digital education has been rejuvenated by customizable online platforms, which have increased the accessibility and cost-effectiveness of academic materials. However, this shift has simultaneously introduced various complications (Kundu, A., & Bej, T. 2021). Educational progression can suffer from a reduction in student enthusiasm and curiosity when direct communication with mentors is absent (Patricia Aguilera-Hermida, A. 2020), a phenomenon that frequently results in premature withdrawal or the total desertion of one's academic goals. Consequently, the degree of student immersion within a pedagogical setting is of paramount importance, given its direct correlation with the speed and depth of knowledge acquisition (Sugden, N., et al., 2021). Learner engagement may be characterized as the integration of a student's affective, physical, and intellectual facets aimed at fulfilling objectives through the alignment of scholastic achievement, tenacity, fulfilment, and communal integration. Furthermore, it serves as a metric for quantifying a student's intensity of participation and exertion (Alruwais, N., & Zakariah, M. 2023). To achieve profound levels of involvement, educational settings must be versatile and responsive, catering to diverse participatory intensities and individual student inclinations to facilitate a comprehensive analysis of their conduct within the pedagogical space. This concept is categorized into four primary spheres: the emotional, the active, the mental, and the agentic.

The intellectual dimension pertains to the psychological immersion in academic tasks, encompassing the drive to acquire knowledge, conceptual clarity, and the resolve to gain expertise. Conversely, the physical dimension concerns the student's direct involvement, diligence, and steadfastness during educational exercises (Bhardwaj, P., et al., 2021).

Despite the increased adaptability offered by virtual schooling, achieving levels of student involvement comparable to traditional face-to-face instruction remains a significant hurdle (Turan, Z., & Karabey, S. C. 2023). The proficiency of educators in utilizing technological tools is paramount for the creation of dynamic digital atmospheres that bolster learner immersion and mitigate feelings of estrangement (ElSayary, A., et al., 2022). Furthermore, individuals who have not cultivated strong autonomous study routines often face inadequate assistance and struggle to gain practical competencies or professional mindsets within applied coursework (Palanci, A., et al., 2024). This stems from the fact that independent educational pursuits represent the most vital component for the successful execution of remote instruction (Hsueh, N.-L., et al., 2022). Within digital education, academic investigations highlight the absence of learner immersion as a precursor to scholastic failure and premature withdrawal. The bulk of scholarly inquiry prioritizes the optimization of educational procedures, student involvement, and the efficacy of instructional delivery and acquisition. Simultaneously, the integration of artificial intelligence has unveiled diverse techniques for augmenting remote instruction, specifically regarding scholastic achievement, digital involvement, and student interest (Ouyang, F., et al., 2022; Balakrishnan, B., & Parivara, S. A. 2023). Furthermore, the scarcity of customized pedagogical tasks designed to meet specific learner needs exacerbates the hurdles to achieving productive educational outcomes (Demong, N. A. R., et al., 2023).

Literature Review

Cagliero, L., et al., (2021) have stated that the escalating adoption and prevalence of virtual instruction, a multitude of scholars have scrutinized how technological integration influences learner involvement and academic results. A significant portion of the literature within this domain asserts that the utilization of digital tools exerts a constructive impact on student immersion. Furthermore, certain investigations indicate that non-simultaneous learning helps students develop higher-order abilities, such as analysis, synthesis, problem solving, judgement, simulation, and teamwork. Students who participate in online learning tend to collaborate better. Ofori, F., et al., (2020) have highlighted that, because online learning has made higher education more accessible, there is now a need for more accountability and proof of learning efficacy. Student involvement is one of the most significant indicators of prosperous digital instruction include high levels of engagement. To guarantee the productivity of this pedagogical approach, prioritizing learner involvement within the virtual environment is of paramount importance. Furthermore, a variety of educational structures for the classroom exist that incorporate modern technical progress.

Lu, K., et al., (2023) have collected responses from 325 learners to explore the factors influencing their willingness to continue participating in asynchronous online learning environments. The investigation focused on four dimensions: internal motivation, external motivation, access to diverse learning resources, and mental involvement in learning activities. The results demonstrated that mental involvement was the only variable that significantly influenced sustained participation in online courses. This finding highlights the crucial role of cognitive involvement in strengthening learners' determination and long-term commitment.

Mohamad Nezami, O., et al., (2020) have attempted to estimate learner involvement by examining emotional responses and facial movements through facial recognition technologies (Savchenko, A. V., et al., 2022; Abdellaoui, B., et al., 2024). The computer vision–based approaches are utilized to evaluate student involvement, emphasizing the impact of emotional states during learning. Engagement levels were estimated using real-time images captured through webcams, where deep learning–driven engagement identification was combined with facial emotion analysis techniques.

Abdellaoui et al., (2024) have developed a Convolutional Neural Network (CNN) using DL techniques, utilizing a dataset comprised of visual recordings and still frames of students at Kenitra, Morocco's Ibn Tofaïl University. The objective of this inquiry was to evaluate student emotional states and degrees of involvement throughout the pedagogical journey. The findings demonstrate that quantifying student contribution and recognizing their affective responses is achievable, thereby facilitating informed choices to bolster educational exchange and knowledge acquisition.

In a separate investigation by Abdellaoui, B., et al., (2024) the identical researchers explored the correlation between escalating withdrawal frequencies and the physical and affective well-being of students. To achieve this, a methodology focused on the examination of recorded student footage was utilized, allowing for the simultaneous assessment of emotional states and the quantification of participatory depth. This strategy integrates sophisticated computational procedures with various automated learning techniques. The subsequent data offers significant perspectives on student encounters, which in turn shapes the instructional strategies implemented by educators.

Casalino, G., et al., (2022) have evaluated the intensity of student immersion through a computational model centered on ocular movement, cranium orientation, and facial gestures. The findings indicated that these predictive models were highly effective at anticipating the level of student attentiveness within the classroom.

Ho, I. M. K., et al., (2021) have proposed a framework utilizing automated regression techniques, demonstrating that curricular distribution, instructional exertion, and a predilection for conventional schooling serve as primary predictive variables. According to Lu, D.-N., et al., (2020) the pedagogical selection of learners was anticipated through the application of a grouping algorithm. In another investigation, Rincon-Flores, E. G., et al., (2022) have employed educational data metrics to examine unique student scholarly personas. Their conclusions indicate that predictive precision is enhanced as the dataset expands, ultimately refining the educational experience and minimizing scholastic under performance.

Deepa, P., & Kumar, M. (2024) have investigated various ML classifiers (Decision Tree (DT), Random Forest (RF), XGBoost) to predict student engagement and adaptability in online courses, finding that properly optimized classifiers (e.g., tuned DT) achieve strong predictive performance of around 90% accuracy on real LMS data, highlighting the importance of model selection and optimization for reliable engagement prediction in real educational settings.

Chen, J., et al., (2025) have performed an extensive literature evaluation, regarding the application of automated computational methods within tertiary schooling to forecast academic achievement, student immersion, and belief in one's own capabilities. According to this assessment, frequently utilized predictive architectures specifically Logistic Regression, Support Vector Machines, RFs, and DT deliver reasonable levels of precision. These particular models are preferred by researchers due to their straightforward nature and the ease with which their results can be explained. However, the study highlights limitations including sensitivity to data quality, inconsistent evaluation metrics, and limited generalization across different learning contexts, indicating the need for more robust and adaptable predictive approaches.

Mandia, S., et al., (2025) have introduced a Transformer-based engagement classification model ("Engage Former") to automatically categorize student engagement from multimodal video signals in online learning contexts. Across several affective state datasets, the model achieved state-of-the-art performance on key benchmarks, highlighting the potential of advanced DL architectures to capture nuanced emotional and behavioural engagement patterns, though performance varies by dataset.

The Table 1 presents a comprehensive overview of prior studies focused on student engagement analysis in online and technology-enhanced learning environments. It systematically compares a range of machine learning, deep learning, statistical, and theory-driven approaches adopted across the literature. For each study, the employed technique, key strengths, inherent limitations, and reported performance outcomes are clearly summarized. The comparison highlights how different methodological choices influence engagement prediction and assessment effectiveness. Overall, the table 1 provides valuable insights into current research trends while helping to identify limitations and potential directions for future work.

Research Gap

The existing studies on student engagement in online learning environments have widely employed ML and DL models; however, the resulting performance remains inconsistent and often inadequate for robust and scalable application. Predominant reliance on standalone models and single-modal engagement data limits the capacity of existing approaches to capture the complex, non-linear, and evolving nature of student behavior. Such modeling strategies frequently exhibit reduced generalizability and sensitivity to contextual variations across learners and platforms. Moreover, the isolated use of individual algorithms fails to leverage the complementary strengths inherent in diverse learning models. Although ensemble learning has been introduced to address some of these limitations, current studies lack a systematic and cohesive multimodal integration framework. A vital void in existing scholarship is exposed here, necessitating a consolidated, multi-component collective strategy. Such a framework would be designed to offset the specific vulnerabilities of isolated algorithms, thereby providing more consistent, precise, and universally applicable forecasts regarding learner immersion within digital educational spaces.

Research Methodology

This study adopts a systematic review–driven and model-oriented research methodology to analyze and synthesize recent advancements in student engagement prediction within online learning environments. Initially, a comprehensive literature selection process is conducted by identifying and screening peer-reviewed studies focusing on student engagement analysis using ML, DL, ensemble learning, and multimodal learning techniques. The

Table 1: Comparative analysis of techniques for student engagement prediction and assessment

Authors	*Technique*	*Strength*	*Limitation*	*Performance*
Deepa, P., & Kumar, M. (2024)	ML classifiers (DT, RF, XGBoost) on LMS data	High accuracy on structured features; interpretable models	Depends on handcrafted features; limited behavioral modeling	High prediction Accuracy
Chen, J., et al., (2025)	Structural Equation Modeling (SEM) based on Self-Determination Theory	Explains psychological drivers of engagement; theoretical grounding	Context limited to video conferencing; less focus on long-term impact	Autonomy and relatedness strongly influence emotional and cognitive engagement
Osmanli Tabriz. (2025)	Hybrid ensemble using Markov Chains, HMMs, and ML classifiers (DT, SVM)	Captures temporal learning patterns and improves engagement prediction through hybrid modeling	Increased model complexity and higher computational cost	Outperforms individual ML and probabilistic models
Mandia, S., et al., (2025)	Transformer-based DL model (EngageFormer) using multimodal video features	Effectively captures temporal, emotional, and behavioral engagement patterns	Performance varies across datasets; high data and computation requirements	State-of-the-art results on multiple benchmarks
Wen, M. (2024)	Use of interactive technologies in online music education	Encourages creative thinking; supports student agency	Limited to music education; may not generalize	Significant increase in student creativity and active participation
Chen, J., et al., (2025)	Systematic review of ML applications for student performance, engagement & self-efficacy	Wide adoption of ML techniques	ML models depend on handcrafted features and show inconsistent performance across datasets	ML models broadly show moderate to high accuracy depending on dataset
Thiering, J., et al., (2025)	Bias-mitigated multi-task DL model for engagement assessment	Enhances fairness and interpretability	Higher model complexity	Effective engagement prediction with reduced bias
Chaudhary, M. K., et al., (2025)	SEM linking design, technology, and engagement	Holistic view of multiple factors influencing engagement	Cross-sectional design limits causal inference	Engagement mediates learning effectiveness; usability is a key driver
Johar, N. A., et al., (2023)	Systematic review of learning analytics studies on student engagement	Showed LA helps track engagement trends and support predictive modeling	Limited to published studies; focused on LMS/MOOC	LA can enhance student learning performance
Brahim, G. B. (2022)	Statistical feature engineering + ML (e.g., SVM, RF)	Introduces novel features (entropy, time-weighted activity)	May require advanced computation and feature tuning	Novel features outperform traditional metrics in grade prediction

reviewed studies are categorized based on data modalities (behavioral logs, video interaction data, assessment records, discussion activity), modelling approaches (traditional ML, deep neural networks, hybrid and ensemble models), and learning objectives. Building upon the identified limitations, this study conceptually designs a multimodal ensemble framework that integrates heterogeneous engagement indicators with student flexibility attributes, including time management patterns, learning regularity, self-regulation behavior, and schedule adaptability. Multiple base learners are combined using ensemble strategies such as bagging, boosting, and stacking to exploit complementary model strengths and enhance prediction robustness, accuracy, and generalizability. Furthermore, a multimodal learning perspective is employed to jointly model diverse data sources, enabling a holistic representation of student behavior. The proposed methodology emphasizes model reliability, scalability, and interpretability, thereby supporting early risk identification, personalized intervention, and data-driven decision-making in online education systems.

Datasets Used

This study employs two rigorously curated educational datasets to investigate student engagement and adaptability in online learning environments. The first dataset, Student Flexibility in Online Courses, captures learners' scheduling preferences, adaptability to course formats, and behavioral tendencies across diverse online learning scenarios. Comprising comprehensive metrics of digital interaction, the subsequent data collection, titled Online Course Engagement, incorporates various indicators such as the regularity of system access, duration spent on assignments, involvement in forum dialogues, and typical behaviors regarding the turn-in of coursework. Collectively, these datasets offer a comprehensive foundation for uncovering behavioural patterns, correlations between flexibility and engagement, and factors influencing learning outcomes in digital education contexts.

Modalities : Behavioural and Interaction Logs

The datasets comprise multiple behavioural and interaction-based modalities that serve as proxies for student engagement. Data include detailed activity logs, clickstream information, and time-stamped course interactions, complemented by self-reported flexibility measures reflecting students' adaptability to various instructional formats and schedules.

Data Preprocessing and Feature Extraction

Each dataset undergoes rigorous preprocessing to ensure data integrity and consistency. Interaction logs are cleaned to remove missing or inconsistent entries, aggregated into standardized temporal intervals, and transformed into feature vectors representing activity intensity, participation frequency, and engagement dynamics. Self-reported flexibility measures are normalized and encoded to align with interaction-based features. These preprocessing and feature engineering steps provide a robust, multimodal representation of student engagement and adaptability, serving as a strong foundation for subsequent ensemble modelling and analysis.

Exploratory Data Analysis (EDA)

For the purpose of achieving a holistic grasp of learner immersion and adaptability within virtual schooling, an EDA was performed. This investigative process focused specifically on the data collections titled Online Course Engagement and Student Flexibility in Online Courses. Descriptive statistics were calculated to summarize critical attributes, including login frequency, time-on-task, discussion participation, assignment submissions, and self-reported flexibility measures. Advanced visualization techniques, such as histograms, boxplots, and scatterplots, were employed to uncover underlying patterns, trends, and potential outliers within the datasets.

Correlation analysis revealed significant associations between flexibility and engagement metrics, indicating that learners with higher adaptability to course schedules exhibited elevated levels of participation and sustained interaction in online activities. These findings provide crucial insights into learner behavior, informing feature selection and shaping the subsequent implementation of ensemble ML and DL models. By systematically uncovering these patterns, the EDA establishes a robust foundation for predictive modeling and the development of a fused multimodal classification framework, ensuring that the proposed approach effectively captures the complex dynamics of online student engagement.

Data Splitting

To ensure robust model evaluation and mitigate overfitting, the datasets were systematically partitioned using a stratified data splitting strategy. Initially, each dataset was divided into training and testing subsets in a conventional 70:30 ratio, preserving the inherent distribution of key variables such as engagement metrics and flexibility indicators. To construct and refine the multi-component collective which integrates both automated learning and neural network methodologies for training data partition was employed. Concurrently, the validation portion directed the choice of architecture and the adjustment of internal parameters. The evaluation of the ultimate integrated model's ability to operate on unfamiliar information was conducted using the testing segment, which remained strictly segregated. Furthermore, the application of stratified partitioning guaranteed that every grouping precisely mirrored the fundamental characteristics of the dataset, preserving the relative balance between students with high levels of involvement and those with minimal participation. This rigorous splitting methodology not only enhances the reliability of the predictive outcomes but also supports reproducibility and comparability across different modelling approaches in the context of online education research. This research work illustrates the combined application of neural network forecasts and automated learning estimations facilitates a more thorough grasp of student adaptability and immersion within virtual educational spaces is the primary emphasis of Figure 1. By merging the results derived from diverse algorithmic architectures, this phase allows for a more profound assessment of educational conduct recorded across various tiers of complexity, extending from organized engagement attributes to intricate chronological sequences. The analysis emphasizes how ensemble integration can balance interpretability and representation power, while mitigating the limitations observed in individual models. Rather than serving as a final decision point, this stage functions as an analytical lens through which the effectiveness, stability, and practical relevance of ensemble-based approaches are assessed, thereby informing future model design and research directions in learning analytics.

Comprehensive ML and DL Modelling for Online Learning Analytics

In order to thoroughly simulate learner immersion and adaptability within virtual pedagogical settings, the refined data collections are subjected to simultaneous examinations via both neural network and automated learning architectures.

ML Framework: To detect fundamental trends and forecast indices of flexibility and participatory intensity,

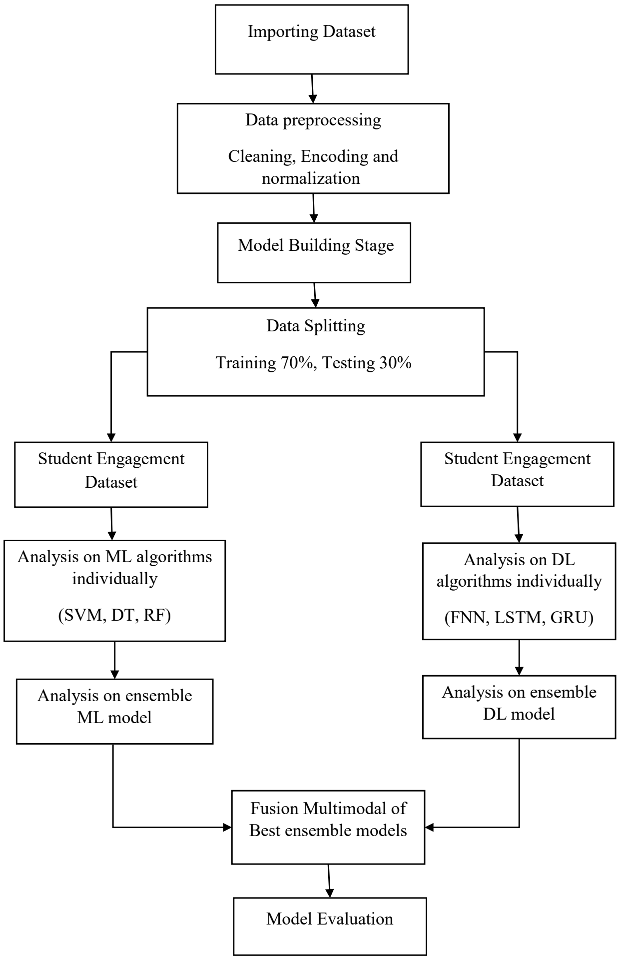

Figure 1: Overall flow diagram of the proposed model

a collection of sophisticated algorithms namely Support Vector Machines, XGBoost, and RF is utilized. Sophisticated feature engineering is conducted to extract salient predictors such as login frequency, assignment submission consistency, duration of interaction with course materials, and participation in discussion forums. Hyper parameter optimization is systematically performed using stratified cross-validation to maximize generalization while minimizing overfitting. The models are evaluated through a spectrum of performance metrics such as accuracy, to ensure robustness and reliability. This approach provides interpretable insights into the most influential factors affecting student behavior, supporting data-driven understanding of online learning dynamics.

Support Vector Machines (SVMs)

SVM are employed to process structured student behavior data derived from Learning Management System (LMS) logs. Features such as task completion rates, time spent on learning activities, click density, and navigation patterns are transformed into feature vectors and used to classify student engagement and flexibility levels. Even when provided with a restricted quantity of categorized data points, Support Vector Machines demonstrate exceptional efficiency and maintain robust functionality within complex, multi-variable attribute dimensions. This makes them suitable for engagement prediction tasks where clean behavioral metrics are available, while also reducing the likelihood of overfitting.

Decision Trees (DTs)

DT function as rule-based classifiers that are well suited for categorical and low-dimensional interaction data, such as login frequency, quiz completion flags, session dropouts, and participation indicators. Their hierarchical decision structure enables transparent interpretation of how individual behavioral features influence engagement and flexibility outcomes. An important advantage of DTs is their interpretability, allowing educators to trace decision paths and derive actionable feedback. Moreover, DTs can handle noisy or incomplete LMS logs and naturally support ensemble extensions such as bagging and boosting.

Random Forest (RF)

RF is a collective learning algorithm in which multiple decision-based models are developed from stochastic portions of data and features, and their independent predictions are merged to obtain the final result. In the context of student engagement analysis, RF effectively captures diverse and heterogeneous learning behaviors across students. By reducing variance and improving generalization, RF enhances prediction stability, particularly in datasets with complex and varied engagement patterns. Its robustness makes it well suited for large-scale online learning environments with mixed behavioral characteristics.

Neural Network Architecture: Concurrently, to identify complex time-based and non-proportional relationships inside the information pools, deep-level configurations specifically Long Short-Term Memory (LSTM) designs and forward-propagating networks are deployed. These models are particularly suited for modelling sequential engagement trends and behavioral fluctuations over the course duration. Input features are normalized and structured to optimize network learning, with regularization strategies such as dropout applied to prevent overfitting. Training is conducted iteratively, with adaptive learning rates and architecture tuning to ensure convergence and stable performance. Model efficacy is assessed using analogous ML metrics along with additional regression-specific indicators such as Mean Absolute Error (MAE).

Feedforward Neural Networks (FNNs)

Feedforward Neural Networks are employed to learn complex non-linear relationships among student engagement attributes such as interaction intensity, content access frequency, and assessment performance. By stacking multiple hidden layers, FNNs automatically learn hierarchical feature representations that may not be explicitly captured by traditional ML models. By utilizing this functionality, the system can detect nuanced participatory dynamics that impact learner immersion and flexibility within digital educational settings.

Long Short-Term Memory (LSTM) Networks

LSTM networks are specifically designed to model temporal and sequential patterns in student behavior data. In online learning scenarios, engagement evolves over time, influenced by course progression, deadlines, and learning fatigue. LSTMs effectively capture such temporal dependencies by retaining long-term contextual information, allowing the model to track changes in engagement and flexibility across different learning phases. This makes LSTMs highly suitable for time-stamped activity logs and longitudinal engagement analysis.

Gated Recurrent Unit (GRU)

GRU networks provide an efficient alternative to LSTM by modeling sequential dependencies with fewer parameters. GRUs balance computational efficiency and performance, enabling faster convergence while still capturing temporal engagement trends. In this study, GRUs help identify short- and medium-term behavioral transitions, such as sudden drops or improvements in student engagement, making them suitable for real-time or large-scale online learning analytics.

By conducting independent ML and DL analyses, this stage ensures a dual-perspective understanding of online learning behaviours that combining the interpretability and feature importance insights from ML with the non-linear, temporal modeling capabilities of DL. The predictions from these models form a robust foundation for the subsequent ensemble strategy, where the complementary strengths of both approaches are synergistically integrated to enhance predictive accuracy and generalization across unseen datasets.

Ensemble Model

To generate a solitary, more dependable conclusion, a collective predictive architecture merges the results from various distinct algorithms. Instead of depending on the constraints or premises of an isolated computational method, this collaborative approach utilizes the variety between configurations to mitigate systematic errors, decrease statistical volatility, and enhance the capacity for universal application. By aggregating predictions from heterogeneous classifiers, ensemble models are widely recognized for achieving superior robustness and stability, particularly in complex real-world datasets where learning patterns are diverse and noisy. To enhance the forecasting of learner adaptability and involvement, a multi-component collective integrates various neural networks and automated learning architectures. Conduct-based, organized attributes including the regularity of system access and finishing of assignments are managed by traditional algorithms such as LR, DTs, and SVM. Concurrently, chronological, intricate trends within the scholarly actions of individuals are identified by deep-level configurations like forward-propagating networks, GRU, and LSTM. The predictions from all models are merged using a weighted aggregation strategy, optimizing each model's contribution based on validation performance. This ensemble approach leverages both interpretability and deep behavioural insights for more accurate predictions.

Effectiveness of the Multimodal Ensemble over Individual Models

The proposed multimodal ensemble consistently outperforms individual ML and DL models by addressing their inherent limitations. While ML models offer transparency and stability, they may struggle to capture long-term temporal dependencies. Conversely, DL models excel at learning sequential and non-linear patterns but may be sensitive to noise and overfitting. The ensemble framework mitigates these weaknesses by selectively amplifying reliable predictions and suppressing unstable outputs. This collaborative learning mechanism results in enhanced prediction accuracy, improved generalization across diverse learner profiles, and greater resilience to data variability. Consequently, the multimodal ensemble provides a more comprehensive and dependable assessment of student engagement and flexibility than any standalone model, making it particularly well suited for dynamic online learning environments.

Formation of the Multimodal Ensemble

In this work, a multimodal ensemble is formed to enhance prediction of student engagement and flexibility. The ensemble combines outputs from multiple models, each capturing unique patterns in the data. Rather than relying on a single approach, the fusion leverages the strengths of all models. Predictions are integrated using a weighted aggregation strategy, where models with higher validation performance contribute more. This approach ensures that the ensemble accounts for diverse behavioral and temporal patterns. By unifying different model insights, the ensemble produces more reliable and robust predictions. Overall, it provides a balanced framework that improves accuracy while maintaining interpretability.

Algorithm for Multimodal Ensemble Learning for Student Engagement and Flexibility Prediction

Input: Integrated online learning dataset

$$D = \{X, y\}$$

- X represents behavioural, interaction, and flexibility features
- y represents student engagement level

Output:

Evaluate prediction of engagement level $\hat{y}$

Step 1: Load dataset D

Step 2: Preprocess X (cleaning, encoding, normalization)

Step 3: Represent features

$$X = \left\{x_b, x_i, x_f\right\}$$

Step 4: Split data

$$D \to D_{train}\left(70\%\right) + D_{test}\left(30\%\right)$$

Step 5: Train ML models

$$\hat{y}_{ML} = f_{ML}\left(X\right)$$

Step 6: Train DL models

$$\hat{y}_{DL} = f_{DL}\left(X_t\right)$$

Step 7: Fuse predictions

$$\hat{y} = w_{ML}\hat{y}_{ML} + w_{DL}\hat{y}_{DL}$$

$$w_{ML} + w_{DL} = 1$$

The proposed algorithm efficiently analyses student engagement by extracting and processing key features from diverse datasets. It leverages predictive modelling to generate actionable insights, ensuring scalability, accuracy, and adaptability for enhancing online learning outcomes.

Mathematical Formulation of the Ensemble Model

Let:

- M_i = Prediction from the i^{th} ML model, $i = 1, 2, \ldots, m$
- D_j = Prediction from the j^{th} DL model, $j = 1, 2, \ldots, n$
- w_i = Weight assigned to the i^{th} ML model
- v_j = Weight assigned to the j^{th} DL model

The final ensemble prediction $\hat{y}$ is computed as a weighted sum:

$$\hat{y} = \sum_{i=1}^{m} w_i \cdot M_i + \sum_{j=1}^{n} v_j \cdot D_j$$

with the normalization constraint:

$$\sum_{i=1}^{m} w_i + \sum_{j=1}^{n} v_j = 1, w_i, v_j \geq 0$$

- $\hat{y}$ = Final predicted engagement or flexibility score
- w_i, v_j are optimized based on validation performance, reflecting the reliability of each model
- The ensemble balances ML and DL contributions to improve accuracy, stability, and generalization compared to individual models

To guarantee that the ultimate forecasts exploit the advantages inherent in every algorithmic category, this proportional collective arrangement is utilized. Consequently, a resilient, explainable, and functional methodology for anticipating learner adaptability and involvement within digital educational settings is established.

Result and Discussion

The experimental analysis reveals that individual ML and DL models, when applied independently to student engagement and flexibility analysis in online courses, capture only partial behavioral patterns and fail to consistently produce optimal results. ML models effectively utilize structured interaction features but show limitations in modeling complex and evolving learner behaviors, while DL models capture temporal and non-linear engagement trends but exhibit sensitivity to data variability and noise. To address these limitations, this study proposes a multimodal ensemble framework that integrates both ML and DL predictions, enabling complementary learning and balanced decision-making. The comparative evaluation, summarized in the performance comparison table, clearly demonstrates that the proposed ensemble model outperforms all standalone ML and DL models across key evaluation criteria. These results confirm that the multimodal ensemble approach provides a more robust, accurate, and generalized solution for analyzing student engagement and flexibility in online learning environments, thereby establishing the proposed model as the most effective framework in this study.

The Table 2 presents a comparative analysis of approaches for predicting student engagement. Ayouni, S., et al., (2024) implemented traditional ML classifiers, including ANN, SVM, and DTs, achieving 85% accuracy, yet these models demonstrated limited capacity to capture the complex and dynamic nature of engagement. Yuan, J., et al., (2022) applied a CNN-based DL model, attaining 83% accuracy with high training performance but reduced generalization on unseen data. The proposed multimodal ensemble, which synergistically integrates ML and DL techniques, outperforms prior methods with a 94% accuracy, effectively addressing the limitations of individual models and offering a more robust and comprehensive representation of student engagement patterns.

Figure 2 presents a clear comparative analysis of the predictive performance of different modelling approaches used to assess student engagement and flexibility in online learning environments. The multimodal ensemble model demonstrates the highest accuracy of 94%, highlighting the effectiveness of integrating ML and DL predictions to capture both structured behavioural patterns and complex temporal dynamics. In comparison, the standalone ML

Table 2: Accuracy comparison of student engagement prediction models

Author/Modal	*Methodology*	*Accuracy*
Ayouni, S., et al., (2021)	ML classifiers (ANN, SVM, DT) for engagement prediction	85%
Yuan, J., et al., (2022)	CNN-based DL for engagement detection	83%
Proposed Multimodal ensemble	ML & DL	94%

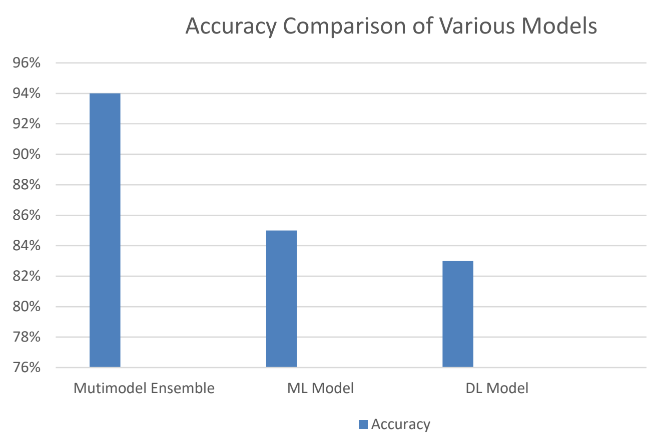

Figure 2: Accuracy performance comparison of multimodal ensemble, ML, and DL models

model achieves an accuracy of around 85%, indicating reasonable performance but limited capacity to model non-linear and multimodal engagement characteristics. The DL model, with an accuracy of approximately 83%, shows strong representation learning capabilities but comparatively lower generalization when applied independently. Overall, the chart clearly indicates that the proposed multimodal ensemble approach significantly outperforms individual ML and DL models, confirming its suitability as a robust and reliable framework for student engagement and flexibility prediction.

Conclusion

This study reviewed and analysed a wide range of ML, DL, and hybrid methodologies applied to the prediction of student engagement and flexibility in online learning environments. The findings indicate that traditional ML models provide interpretability and stable performance on structured behavioural data, whereas DL approaches are effective in learning complex and temporal patterns but often face challenges related to generalization and data dependency. The comparative analysis across recent studies suggests that integrating multiple modelling paradigms can potentially address the individual limitations observed in standalone approaches. In this context, multimodal and ensemble-based frameworks emerge as a promising direction, as they combine complementary strengths of ML and DL models and demonstrate improved performance trends in the literature. While further empirical validation is required, the surveyed evidence indicates that such integrated approaches may offer more robust and scalable solutions for engagement and flexibility analysis, thereby opening avenues for future research in intelligent and adaptive online learning systems.

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