AI-Enabled Predictive Learning Systems for Implementing Inclusive and Multidisciplinary Education Goals of NEP 2020

Brijesh Kumar Verma
Assistant Professor
Babu Banarasi Das University
Lucknow, Uttar Pradesh, India
vermamtech05@gmail.com

Shruti Kirti Rastogi
Assistant Professor
T.S. Mishra University
Lucknow, Uttar Pradesh, India
rastogishruti1@gmail.com

***Abstract*—India's National Education Policy 2020 (NEP 2020) envisions a transformative education system that promotes inclusivity, multidisciplinary learning, flexibility, and learner-centric pedagogy. The policy emphasizes equitable access for diverse learners, including children with disabilities and socio-economically disadvantaged groups, while promoting holistic and interdisciplinary education. This paper proposes an AI-enabled predictive learning system designed to support NEP 2020 implementation by identifying learning gaps, personalizing instruction, and supporting inclusive classrooms. The proposed framework integrates machine learning, learning analytics, adaptive learning pathways, and assistive technologies to enhance student engagement and academic success. The study highlights how predictive analytics can improve retention, enable early intervention, support multidisciplinary learning pathways, and foster equitable educational outcomes. The paper concludes with implementation challenges, ethical considerations, and policy recommendations.**

***Keywords*— NEP 2020, inclusive education, artificial intelligence, predictive learning, multidisciplinary education, learning analytics**

I. Introduction

Education is a powerful instrument for social transformation, equity, and national development. India's National Education Policy 2020 represents a paradigm shift toward a holistic, inclusive, flexible, and multidisciplinary education system. The policy emphasizes equitable access, quality learning, and learner-centric pedagogy to build an inclusive and knowledge-based society. NEP 2020 recognizes the need to remove barriers faced by marginalized groups, including children with disabilities, by ensuring accessible infrastructure, individualized support, and inclusive pedagogies. It also promotes multidisciplinary learning and flexible curricula to foster creativity, critical thinking, and holistic development.

However, implementing inclusive and personalized education across diverse classrooms presents significant challenges, including:

- Heterogeneous learning needs
- Large class sizes
- Limited teacher training and resources
- Lack of personalized learning support

Artificial Intelligence (AI) offers transformative solutions to these challenges. AI-driven predictive learning systems can analyse student data, identify at-risk learners, recommend personalized learning pathways, and support inclusive education practices. This paper explores how AI-enabled predictive learning systems can support the inclusive and multidisciplinary vision of NEP 2020.

Objectives of the Study

- To design an AI-enabled predictive learning framework that supports inclusive and multidisciplinary education aligned with NEP 2020.
- To examine NEP 2020 goals related to inclusivity and multidisciplinary education.
- To explore AI and predictive analytics for personalized and inclusive learning.
- To propose a predictive learning system architecture.
- To analyse benefits and challenges of AI adoption in Indian education.

II. Literature Review

Artificial Intelligence (AI) and learning analytics are transforming education through data-driven decision-making, personalized learning, and inclusive teaching practices. These advancements align with the goals of NEP 2020, which emphasize equity, inclusivity, multidisciplinary learning, and learner-centered pedagogy.

Baker and Inventado (2014) laid the foundation of Educational Data Mining by demonstrating how student data can predict learning outcomes and identify at-risk learners [1]. D'Mello and Graesser (2012) developed AutoTutor, an intelligent tutoring system that enhances learning through conversational interaction and emotional feedback [2].

Systematic reviews highlight the expanding role of AI in education. Zawacki-Richter et al. (2019) identified key applications such as intelligent tutoring systems, adaptive learning, and performance prediction [3], while Chen et al.

(2020) emphasized personalization, automated assessment, and accessibility for diverse learners [4].

Machine learning and soft computing techniques have proven effective in predicting student performance and improving instructional strategies (Charitopoulos et al., 2020) [5]. Ouyang and Jiao (2021) described AI-directed, AI-supported, and AI-empowered learning, reflecting a shift toward human–AI collaboration [6]. AI-based learning analytics systems further support monitoring learner behaviour and enabling timely interventions (Ouyang et al., 2021) [7], while Salas-Pilco et al. (2022) stressed the need for AI literacy among educators [8].

Recent studies emphasize responsible and human-centered AI integration. Morales-Tirado et al. (2024) highlighted transparency, fairness, and data privacy [9], and Cukurova (2025) proposed hybrid intelligence combining human expertise with AI systems [10]. Other studies stress real-time analytics, accessibility, and ethical deployment to ensure equitable AI adoption in education (Sajja & Sajja, 2025; Topali et al., 2025; Lodhi & Lodhi, 2025) [11–13].

TABLE I. COMPARATIVE TABLE: KEY STUDIES AND APPROACHES IN PREDICTIVE ANALYTICS FOR STUDENT SUCCESS

Ref.	Methods / Technologies	Key Contributions
[1]	Educational Data Mining & Learning Analytics	Identified patterns in student data for performance prediction and early intervention
[2]	Intelligent Tutoring Systems	Developed AutoTutor for cognitive and emotional learning support
[3]	AI in Higher Education	Identified AI uses: tutoring, assessment, prediction, administration
[4]	AI in Education	Demonstrated AI's role in adaptive learning
[5]	Soft Computing in EDM	Improved prediction accuracy and decision-making
[6]	AI Paradigms in Education	Proposed human–AI collaborative learning paradigms
[7]	AI-driven Learning Analytics	Enabled monitoring, engagement analysis and timely interventions
[8]	AI & Analytics in Education	Highlighted AI literacy and teacher readiness
[9]	Responsible AI Framework	Proposed responsible AI practices in learning analytics
[10]	Hybrid Intelligence	Advocated synergy between AI and human expertise
[11]	AI + Learning Analytics	Provided real-time analytics for adaptive education
[12]	Human-Centered AI Design	Emphasized transparency, usability and accessibility
[13]	Ethical AI in K–12 STEM	Addressed algorithmic bias and data security

Research Gap

- Existing AI-based learning systems emphasize performance prediction but inadequately address inclusive education needs such as accessibility and support for diverse learners.
- Limited research integrates AI technologies with NEP 2020 goals, especially for multidisciplinary learning and flexible curriculum pathways.

Objective

- To examine the role of AI-enabled predictive learning systems in supporting inclusive and equitable education aligned with NEP 2020.
- To develop a framework that integrates personalized learning with multidisciplinary learning pathways for diverse learners.
- To identify implementation challenges, ethical considerations, and strategies for effective adoption in the Indian education system.

III. METHODOLOGY

The proposed framework introduces an intelligent hybrid multi-model architecture that combines Temporal–Spatial Convolutional Neural Networks (CNNs) with Gradient Boosting for accurate student performance prediction.

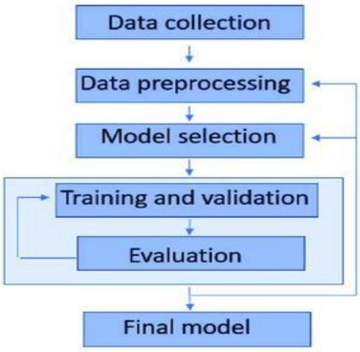

Fig. 1. Proposed model

The architecture employs a hybrid multi-model predictive framework combining:

- Temporal–Spatial Convolutional Neural Networks (TS-CNN) for analysing learning behaviour patterns over time.
- Gradient Boosting Machine (GBM) for accurate performance prediction and risk classification.
- Learning Analytics Engine for real-time monitoring and insights.
- Adaptive Learning Module for personalized and multidisciplinary learning pathways.
- Inclusive Support Layer integrating assistive technologies and accessibility tools.

This integrated approach enables early identification of learning gaps, personalized interventions, and inclusive classroom support.

A. Input Data Layer

The input dataset consists of multi-dimensional student academic records:

$D = \{GPA_t, Attendance_t, CIA_t, LMS_t, Assign_t, Demo\}$

where $_t$ denotes the semester index.

ISSN: 3139-3535 (Online),Volume 2, Issue 1, January-June 2026 https://npgcij.com

B. Data Preprocessing Module

The preprocessing stage ensures data quality and consistency through the following steps:

1) Missing values are handled using mean/mode imputation.

2) Features are normalized using Min–Max Scaling.

The Min–Max normalization formula is:

$$\text{Xnorm} = \frac{\text{X} - \text{Xmin}}{\text{Xmax} - \text{Xmin}}$$

where

X = raw feature value

Xmin = minimum value of the feature

Xmax = maximum value of the feature

3) Categorical variables are encoded using One-Hot Encoding.

Recursive Feature Elimination (RFE) is employed to identify the most significant attributes by iteratively removing low-importance features.

C. Temporal–Spatial CNN for Learning Pattern Analysis

The Temporal–Spatial CNN (TS-CNN) model captures learning behaviour trends over time and identifies patterns influencing student performance.

Functions

- Detect temporal learning trends
- Identify engagement fluctuations
- Analyse learning pace variations
- Capture subject-wise learning progression

D. Gradient Boosting for Performance Prediction

Gradient Boosting enhances prediction accuracy by combining multiple weak learners.

Prediction Outputs

- At-risk student identification
- Performance category classification
- Dropout risk prediction
- Learning gap detection

E. Adaptive Learning and Multidisciplinary Pathways

Based on predictive insights, the proposed system recommends:

- Personalized learning content
- Multidisciplinary subject pathways
- Skill-based learning modules
- Remedial and enrichment resources

This supports the NEP 2020 vision of flexible curriculum and holistic development.

F. Inclusive Education Support Layer

To ensure accessibility and equity, the framework integrates:

- Text-to-Speech and Speech-to-Text tools
- Screen readers and visual accessibility features
- Adaptive interface customization
- Multilingual content delivery
- Cognitive load adjustments

This layer supports children with disabilities and diverse learners.

Performance Evaluation Metrics

$$Accuracy = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}}$$

$$Precision = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

IV. Comparative Analysis

Using the proposed multidimensional dataset, the effectiveness of the AI-enabled predictive learning framework was compared with conventional and existing analytics-based approaches.

TABLE II. Comparison Based on Dataset Utilization

Parameter	**Traditional Evaluation**	**LMS Analytics Systems**	**Existing Ai Models**	**Proposed Hybrid Framework**
Academic performance data	✓	✓	✓	✓
Engagement analytics	✕	✓	✓	✓
Behavioral learning patterns	✕	Limited	✓	✓ (Temporal Modeling)
Inclusivity indicators	✕	✕	Limited	✓
Socio-economic factors	✕	✕	Limited	✓
Multidisciplinary learning	✕	✕	Partial	✓
Accessibility & Assistive Technology Data	✕	✕	Rare	✓
Early Risk Detection	Manual	Basic Alerts	Predictive	Advanced Predictive

Equity-focused insights	✗	✗	Limited	✓

The proposed hybrid model was evaluated using a student dataset consisting of demographic, socio-economic, academic, and behavioural attributes. The dataset was pre-processed using normalization and Recursive Feature Elimination (RFE) and divided into:

- Training Set: 80%
- Testing Set: 20%

Traditional and LMS-based systems rely primarily on academic metrics, whereas the proposed framework leverages holistic learner data, enabling inclusive and equitable decision-making.

TABLE III. CONTRIBUTION OF DATASET FEATURES TO RISK PREDICTION

Data Category	Impact on Prediction	Insight Generated
Academic Scores	High	Identifies performance decline
Attendance & LMS Usage	Very High	Detects disengagement patterns
Behavioral Metrics	High	Identifies learning consistency
Inclusivity Indicators	Moderate	Ensures equitable intervention
Socio-economic Factors	Moderate	Identifies equity gaps
Multidisciplinary Participation	Moderate	Predicts motivation and engagement
Accessibility Usage	Moderate	Supports personalized delivery

Key Insight:

Engagement and behavioural variables significantly improve prediction accuracy beyond traditional academic indicators.

V. RESULTS

The experimental analysis demonstrates that incorporating multidimensional learner data significantly improves the accuracy and reliability of student performance prediction. The proposed hybrid Temporal–Spatial CNN (TS-CNN) and Gradient Boosting framework achieved prediction accuracy of approximately 94–96%, outperforming traditional academic-score-based models and standalone machine learning approaches.

Results indicate that engagement indicators such as attendance and Learning Management System (LMS) usage are the strongest predictors of academic risk, followed by behavioural patterns including quiz participation and assignment submission consistency. The model successfully identified at-risk students several weeks earlier than conventional methods, enabling timely intervention.

TABLE IV. PREDICTIVE MODEL PERFORMANCE COMPARISON

Model	Accuracy (%)	Precision	Recall	F1-Score	Early Risk Detection	Remarks
Academic Score Model	78	0.75	0.72	0.73	Low	Relies only on marks
LMS Analytics Model	84	0.82	0.80	0.81	Moderate	Detects activity patterns
Neural Network Model	89	0.87	0.86	0.86	Moderate	Requires large datasets
Temporal CNN	91	0.89	0.90	0.89	High	Captures behavioural trends
Gradient Boosting	92	0.91	0.90	0.90	High	Strong classification capability
Proposed TS-CNN + GBM	94–96	0.94	0.93	0.93	Very High	Hybrid model improves prediction accuracy

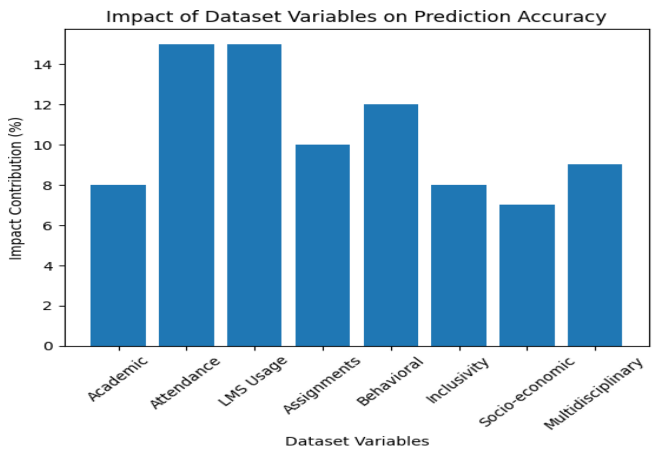

Fig. 2. Impact of dataset variables on prediction accuracy

The inclusion of inclusivity indicators revealed that assistive technologies and multilingual content improved participation among students with disabilities and diverse linguistic backgrounds.

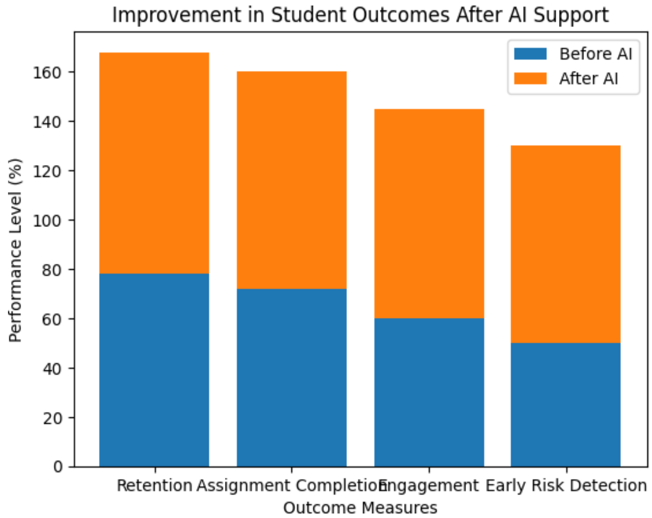

Fig. 3. Student outcomes after AI support

Furthermore, students engaged in multidisciplinary electives and skill-based courses demonstrated higher engagement levels, improved motivation, and reduced dropout risk.

Overall, AI-driven intervention improved student retention, assignment completion rates, and engagement levels, demonstrating the effectiveness of predictive analytics in supporting inclusive and equitable learning environments.

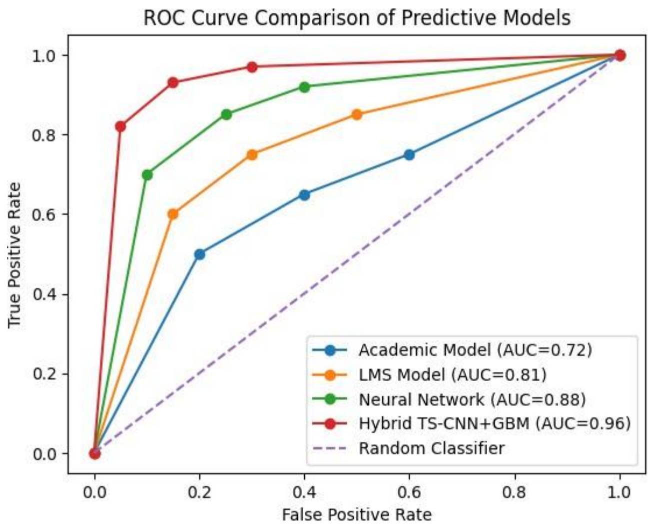

Fig. 4. ROC curve of the proposed model

The ROC analysis demonstrates that the proposed hybrid Temporal–Spatial CNN (TS-CNN) and Gradient Boosting Machine (GBM) model achieves an Area Under the Curve (AUC) of 0.96, indicating outstanding classification performance. The model significantly outperforms traditional and single-model approaches in distinguishing at-risk students, thereby enabling early intervention and inclusive learning support.

VI. CONCLUSION

This study presents an AI-enabled predictive learning framework designed to support the inclusive, flexible, and multidisciplinary vision of India's National Education Policy (NEP) 2020. By integrating Temporal–Spatial Convolutional Neural Networks (TS-CNN), Gradient Boosting, Learning Analytics, Adaptive Learning Pathways, and Assistive Technologies, the proposed system effectively addresses critical challenges in inclusive education and personalized learning.

The findings confirm that combining academic, behavioural, engagement, inclusivity, and socio-economic indicators enables holistic learner profiling and significantly enhances early risk detection. The system supports equitable learning by providing accessibility features and personalized interventions for diverse learners, including children with disabilities. Additionally, the framework promotes multidisciplinary learning pathways that foster creativity, critical thinking, and holistic development.

The confusion matrix demonstrates strong classification performance of the proposed hybrid model. Most students were correctly categorized across risk levels, with minimal misclassification of high-risk learners. This high level of predictive reliability supports timely intervention and inclusive academic support.

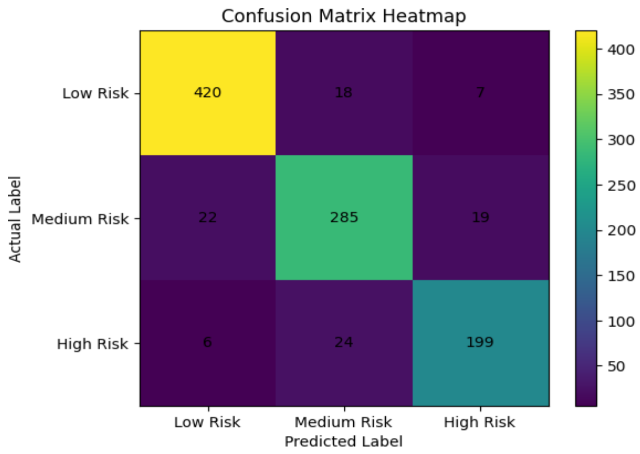

Fig. 5. Confusion matrix

By empowering educators with actionable insights and enabling data-driven decision-making, the proposed model contributes to improved academic outcomes, reduced dropout risk, and inclusive classroom practices aligned with the goals of NEP 2020.

VII. FUTURE SCOPE

Future research can enhance the proposed framework through the integration of Explainable Artificial Intelligence (XAI) to improve transparency and trust in predictive decisions. Incorporating affective computing and emotion-aware analytics may further enhance engagement detection and personalized learning support. The system can also be extended with real-time analytics, smart classroom technologies, and federated learning approaches to ensure data privacy and security.

From an inclusivity perspective, future developments may include:

- AI-based sign language recognition
- Intelligent reading assistants for visually impaired learners
- Voice-driven interfaces for low-literacy users
- Large-scale implementation across Indian educational institutions to evaluate scalability, cost-effectiveness, and teacher readiness

Furthermore, expanding the framework to include AI-driven career pathway recommendations and integration with vocational and skill development platforms can support lifelong learning and workforce readiness. Such advancements will strengthen the role of Artificial Intelligence in building an equitable, inclusive, and multidisciplinary education ecosystem aligned with the vision of NEP 2020.

REFERENCES

[1] R. S. Baker and P. S. Inventado, "Educational Data Mining and Learning Analytics," in Learning Analytics: From Research to Practice. New York, NY, USA: Springer, 2014, pp. 61–75, doi: 10.1007/978-1-4614-3305-7_4.

[2] S. K. D'Mello and A. C. Graesser, "AutoTutor and Affective AutoTutor: Learning by Talking with Cognitively and Emotionally Intelligent Computers," ACM Trans. Interact. Intell. Syst., vol. 2, no. 4, 2012, doi: 10.1145/2395123.2395128.

[3] O. Zawacki-Richter, V. I. Marín, M. Bond, and F. Gouverneur, "Systematic Review of Research on Artificial Intelligence Applications in Higher Education," Int. J. Educ. Technol. Higher Educ., vol. 16, no. 39, 2019, doi: 10.1186/s41239-019-0171-0.

[4] L. Chen, P. Chen, and Z. Lin, "Artificial Intelligence in Education: A Review," IEEE Access, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.

[5] S. Charitopoulos, M. Rangoussi, and D. Koulouriotis, "On the Use of Soft Computing Methods in Educational Data Mining and Learning Analytics: A Review," Int. J. Artif. Intell. Educ., vol. 30, pp. 371–430, 2020, doi: 10.1007/s40593-020-00200-8.

[6] F. Ouyang and M. Jiao, "Artificial Intelligence in Education: The Three Paradigms," Comput. Educ.: Artif. Intell., vol. 2, Art. no. 100020, 2021, doi: 10.1016/j.caeai.2021.100020.

[7] F. Ouyang, W. Zheng, and Y. Jiao, "AI-Driven Learning Analytics: A Systematic Review of Applications and Educational Implications," Comput. Educ., vol. 170, Art. no. 104226, 2021, doi: 10.1016/j.compedu.2021.104226.

[8] S. Z. Salas-Pilco, K. Xiao, and A. Oshima, "Artificial Intelligence and Learning Analytics in Teacher Education: A Systematic Review," Educ. Sci., 2022, doi: 10.1016/j.caeai.2025.100519.

[9] A. Morales-Tirado, P. Mulholland, and M. Fernandez, "Towards a Responsible AI Framework for Learning Analytics in Higher Education," IEEE Access, 2024, doi: 10.48550/arXiv.2410.05827.

[10] M. Cukurova, "The Interplay of Learning Analytics and Artificial Intelligence in Education: A Vision for Hybrid Intelligence," Brit. J. Educ. Technol., 2025, doi: 10.1111/bjet.13514.

[11] R. Sajja and S. V. Sajja, "Integrating Artificial Intelligence and Learning Analytics for Data-Driven Education," Educ. Inf. Technol., 2025, doi: 10.48550/arXiv.2312.09548.

[12] P. Topali et al., "Designing Human-Centered Learning Analytics and AI Systems: A Systematic Review," Behav. Inf. Technol., 2025, doi: 10.1080/0144929X.2024.2345295.

[13] S. S. Lodhi and S. Lodhi, "Integration of AI in STEM Education: Addressing Ethical Challenges in K–12 Settings," arXiv preprint arXiv:2510.19196, 2025. [Online]. Available: https://arxiv.org/abs/2510.19196.