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INNOVATION



HEALTHCARE



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SUSTAINABLE
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VIKSIT BHARAT

PART
2

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Chapter 10: Inclusive Education Practices and Social Participation among Diverse Learners

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Abstract— Inclusive education increasingly requires attention not only to physical and curricular access but also to the quality of learners' social participation within heterogeneous educational environments. This study investigates how inclusive pedagogical practices, AI-supported accessibility mechanisms, adaptive learning environments, and peer-oriented classroom strategies can influence social participation among learners with diverse educational needs. A central research gap is identified in the limited integration of social participation indicators with technology-supported and data-informed models of inclusive education. Existing studies frequently evaluate accessibility, personalization, academic achievement, or attitudes toward inclusion, while comparatively fewer examine peer interaction, group membership, social acceptance, collaborative involvement, and learner agency as interconnected outcomes. The proposed research therefore conceptualizes social participation as a multidimensional construct that can be examined through behavioral, relational, perceptual, and technology-mediated indicators. Particular attention is given to the potential of artificial intelligence and learning analytics to identify participation disparities while avoiding deficit-oriented profiling and algorithmic discrimination. **Keywords—** Inclusive Education, Social Participation, Diverse Learners, Artificial Intelligence, Learning Analytics, Educational Accessibility

Introduction

Inclusive education has developed from a predominantly placement-oriented concept into a broader educational principle concerned with participation, equity, belonging, accessibility, and meaningful engagement. Merely enrolling learners with different abilities, linguistic backgrounds, cognitive profiles, socioeconomic circumstances, or educational support requirements in the same institution does not necessarily produce inclusion. Genuine inclusion requires learners to be recognized as active members of the educational community and to experience opportunities for academic contribution, peer interaction, decision-making, collaboration, and social acceptance.

This distinction between **being present** and **participating meaningfully** has become particularly important in contemporary educational systems. Diverse learners may occupy the same classroom while experiencing markedly different levels of friendship, peer visibility, group involvement, classroom agency, or social recognition. Evidence from research on learners with special educational needs indicates

that access to mainstream classrooms does not automatically eliminate disadvantages in peer relationships and social participation. A recent scoping review synthesizing 63 empirical studies identified joint activities, social behavior, peer relationships, and social self-perception as major dimensions of social participation and reported persistent participation difficulties among learners with special educational needs.

The period following the large-scale digitalization of education has added another dimension to this problem. Between 2021 and 2026, educational institutions have increasingly adopted learning-management platforms, automated transcription, adaptive content systems, speech technologies, recommendation tools, learning analytics, generative artificial intelligence, and other digitally mediated instructional resources. These developments can remove barriers that previously prevented some learners from accessing instructional material. Captioning can support learners who cannot fully access spoken instruction, text-to-speech technologies may assist learners with reading or visual difficulties, adaptive interfaces can modify instructional presentation, and digital collaboration environments can offer alternative channels for classroom contribution.

Technology, however, does not guarantee inclusion. UNESCO's 2023 Global Education Monitoring Report emphasizes that educational technology should be evaluated in relation to equity, relevance, sustainability, and learner needs, while preserving the fundamentally human and social character of education. The report also cautions that unequal technology access and insufficient evidence regarding educational technology can reproduce rather than eliminate disadvantage. Consequently, the critical question is no longer whether technology can provide access but whether digitally supported inclusive practices improve learners' capacity to **participate socially and relationally**.

This distinction creates an important research opportunity. Much of the current literature on artificial intelligence and inclusive education concentrates on personalization, accessibility, assistive functionality, learning achievement, or technology acceptance. A 2024 systematic review of AI and virtual reality applications for students with disabilities reported substantial potential for personalized and accessible educational experiences while also identifying unresolved implementation and ethical challenges. Similarly, Rice and Dunn's systematic review of artificial intelligence involving students with identified disabilities noted that the available evidence remained limited and cautioned against technological approaches that frame learners primarily as burdens to be managed rather than individuals whose agency should be strengthened.

At the same time, research on social participation tends to employ sociometric measures, observation, self-report scales, interviews, or teacher judgments without fully exploiting the emerging possibilities of responsible learning analytics. Research on learning analytics and disability has itself remained comparatively underdeveloped. Khalil, Slade, and Prinsloo's systematic review identified only 26 studies in its final corpus and observed that research connecting learning analytics with inclusiveness and disability was still limited, particularly outside higher education. Their analysis also highlighted concerns regarding surveillance, accessibility, discrimination, and the possibility that data-driven systems may advantage some groups while marginalizing others.

Research Gap and Study Focus

The distinctive gap addressed in this manuscript lies at the intersection of these two research traditions. **Inclusive-education research has developed sophisticated accounts of peer relationships and participation but rarely integrates them with AI-enabled learning analytics, while AI-based inclusion research frequently measures accessibility or academic performance without adequately modeling social participation as a multidimensional educational outcome.**

This separation limits the ability of institutions to determine whether supposedly inclusive practices actually produce equitable classroom relationships. For example, an adaptive system may successfully provide accessible learning materials to a learner with a disability while that learner remains isolated during collaborative activities. Likewise, a student may demonstrate adequate academic engagement within a digital platform but occupy a peripheral position within peer interaction networks. Conventional academic indicators would characterize both situations as successful participation even though the learner's social inclusion remains incomplete.

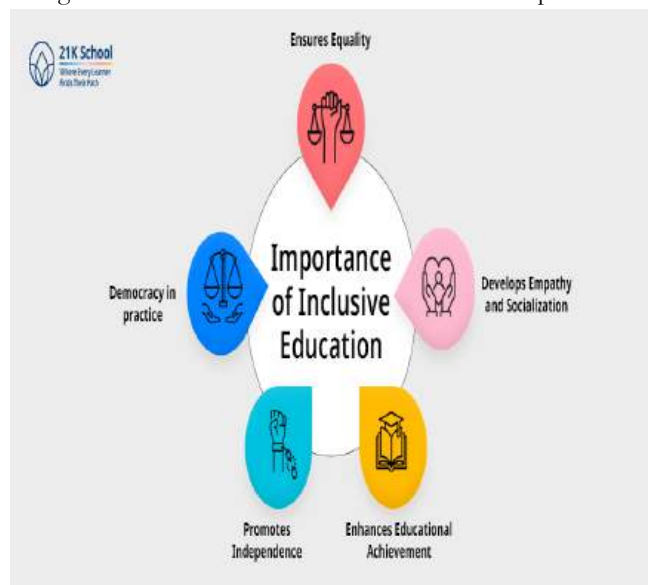


Fig. 1: Inclusive Education in India

Source: <https://www.21kschool.com/in/blog/inclusive-education-in-india/>

The present study therefore proposes a conceptual shift from **access-centered inclusion** toward **participation-sensitive**

inclusion. Inclusive education practices are treated as an interconnected system comprising differentiated instruction, universal accessibility, peer collaboration, teacher facilitation, learner choice, supportive classroom climate, assistive technology, and adaptive digital resources. Social participation is conceptualized through multiple dimensions including peer interaction, collaborative involvement, perceived belonging, social acceptance, classroom agency, and participation regularity.

Artificial intelligence is positioned within this framework as an analytical and supportive technology rather than an autonomous decision-maker. Machine-learning models may help detect patterns of unequal participation, but any prediction regarding social marginalization must remain interpretable, privacy-aware, and subordinate to professional educational judgment. This orientation is particularly important because social participation is context-dependent and cannot be reduced to raw interaction frequency. A learner who contributes less frequently may nevertheless experience strong peer acceptance, whereas frequent digital activity may coexist with weak interpersonal belonging.

Accordingly, the primary objective of the manuscript is to examine the relationship between inclusive education practices and social participation among diverse learners while developing a data-informed framework capable of detecting participation disparities across heterogeneous learner profiles. The study further seeks to determine which dimensions of inclusive practice are most strongly associated with social participation and whether multimodal educational indicators can improve identification of learners at risk of social marginalization without reducing diversity to diagnostic labels. The research is therefore guided by three interconnected questions: How strongly do inclusive educational practices predict social participation among diverse learners? Which instructional, relational, accessibility, and technology-supported practices contribute most substantially to participation and belonging? Finally, can an interpretable machine-learning framework identify patterns of restricted social participation more effectively than conventional single-score educational assessment?

Literature Review

Inclusive Education as Participation Rather Than Placement

Modern scholarship increasingly distinguishes structural integration from authentic inclusion. Structural integration concerns access to ordinary educational settings, whereas authentic inclusion concerns whether learners can participate, influence classroom activities, establish meaningful relationships, and experience membership within the learning community.

Subban, Woodcock, Sharma, and May's systematic review of students' experiences of inclusive secondary education identified supportive relationships, positive teacher and school-leader beliefs, supportive teaching practices, and accessibility among the major conditions facilitating inclusion. These findings indicate that inclusion emerges through interaction

among institutional culture, pedagogy, relationships, and accessibility rather than through a single accommodation.

Social participation provides an especially useful indicator because it captures whether educational inclusion becomes visible within everyday interactions. Studies commonly distinguish several dimensions, including friendships, social contact, peer acceptance, participation in joint activities, social behavior, and learners' own perceptions of belonging. Research involving students with autism spectrum disorder, for instance, has shown that students in general education environments can continue to experience weaker peer interaction and participation, particularly at the secondary-school level.

Such evidence illustrates why academic achievement alone is insufficient for evaluating inclusive education. A learner may meet curriculum objectives while experiencing persistent interpersonal isolation. Conversely, participation in cooperative learning and classroom decision-making may strengthen belonging even when learning support remains necessary. The effectiveness of inclusion therefore requires simultaneous consideration of academic and social outcomes.

Peer Relationships and Classroom Interaction

Peer relationships represent one of the most consistent determinants of meaningful inclusion. Social interaction provides learners with opportunities to exchange ideas, develop communication skills, negotiate differences, establish friendships, and gain recognition as members of a group. For learners who require additional educational support, the structure of peer interaction may either reduce or reinforce social boundaries.

Research indicates that teachers can deliberately influence these patterns through cooperative tasks, heterogeneous grouping, peer-mediated instruction, shared responsibilities, and structured opportunities for contact. A qualitative evaluation of the FRIEND-SHIP intervention implemented in Greek and Portuguese elementary classrooms found that participating teachers perceived improvements in students' social skills and classroom climate, with benefits reported for students with disabilities and learners from racial or ethnic minority backgrounds.

Peer-mediated interventions are particularly relevant because they redistribute responsibility for inclusion from an exclusive teacher–student relationship toward the wider classroom community. A systematic review by Travers and Carter demonstrated that peer-mediated approaches can generate social and academic benefits while also emphasizing the importance of examining outcomes for peers without disabilities rather than treating them merely as intervention agents. This reciprocal perspective is essential to the present study because social inclusion should transform interaction patterns across the entire classroom rather than operate as an isolated intervention for selected learners.

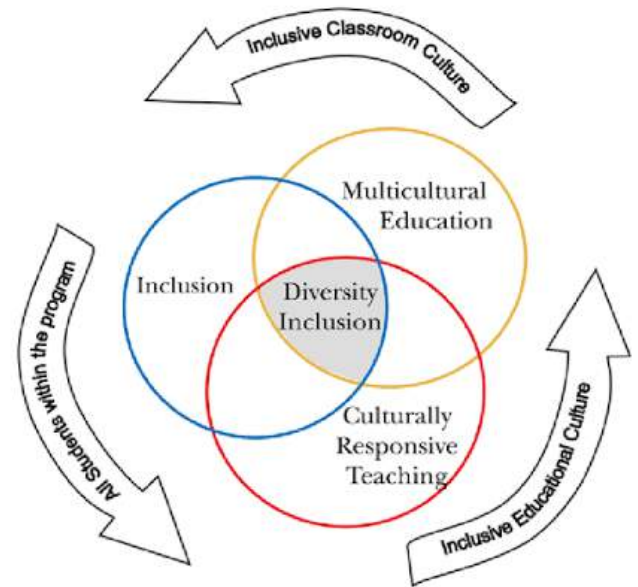


Fig. 2: Diversity Inclusive Program Model

Source: https://www.researchgate.net/figure/The-Diversity-Inclusive-Program-Model-LaVergne-2008_fig1_276227449

Teacher knowledge also matters. Evidence from mainstream primary classrooms suggests that teacher understanding of particular special educational needs can be associated with students' academic achievement and social participation. Teachers influence not only instructional differentiation but also peer grouping, behavioral expectations, opportunities to speak, responses to exclusion, and the degree to which difference is normalized within classroom activities.

Learner Agency and Perceived Belonging

Quantitative interaction counts alone cannot fully represent social participation. Learners' perceptions of belonging, autonomy, recognition, and agency are equally important because participation can appear satisfactory to observers while being experienced as restrictive by the learners themselves.

Qualitative research involving learners with special educational needs has demonstrated that students interpret participation in relation to learning environments, social experiences, relationships, and personal strengths. Research examining students with special educational needs in a Macau secondary school similarly foregrounded participation, group membership, and agency as meaningful components of inclusive educational experience.

These findings support a multidimensional analytical strategy. Social participation should not be represented by one composite score without examining its internal dimensions. Interaction frequency, peer acceptance, group contribution, perceived belonging, and learner agency may vary independently. This distinction becomes especially important when artificial intelligence is introduced because machine-learning systems tend to prioritize measurable behaviors. A participation model that relies solely on clicks, messages, attendance, or speaking turns could misclassify quiet but socially integrated learners while overlooking learners who exhibit high digital activity but low relational belonging.

Artificial Intelligence and Assistive Inclusion

Artificial intelligence has expanded the technological repertoire available for inclusive teaching. Recent applications include speech recognition, automatic caption generation, text simplification, adaptive assessment, intelligent tutoring, predictive analytics, language support, personalized recommendation, image description, and conversational assistance. Such systems may reduce barriers when they are designed around accessibility rather than retrofitted after development.

Systematic reviews published during the recent expansion of educational AI indicate that AI can enhance accessibility and personalization for students with disabilities. At the same time, these reviews repeatedly identify concerns involving infrastructure, teacher preparedness, bias, ethics, privacy, and uneven evidence regarding long-term effectiveness.

The educational significance of these tools should therefore be evaluated beyond technical accuracy. A system may correctly generate captions yet fail to increase a learner's participation in collaborative discussion. An adaptive tutor may improve individual task completion while unintentionally reducing opportunities for peer interaction. Technologies designed for individual personalization can therefore produce a paradox: greater individual accessibility may coexist with reduced collective participation when learners interact more with software and less with peers.

This issue is consistent with UNESCO's recommendation that digital technology complement rather than displace human interaction. Within inclusive education, the principle is particularly important because relationships themselves constitute an educational outcome.

Learning Analytics and Participation-Sensitive Inclusion

Learning analytics provides a potential bridge between inclusive practice and social participation. Data from learning platforms, collaborative activities, participation logs, classroom observations, self-report instruments, and peer networks can potentially reveal patterns that conventional assessment overlooks. Khalil, Slade, and Prinsloo argue that learning analytics has potential to identify disadvantages, evaluate accessibility, and support marginalized learners, but they also demonstrate that empirical research on inclusiveness remains limited.

The central methodological challenge involves deciding what should be measured. Conventional learning analytics often concentrates on achievement, persistence, resource access, assessment behavior, or dropout risk. Social participation requires additional relational information. Network position, reciprocity of interaction, diversity of peer contacts, participation across group activities, perceived belonging, peer acceptance, and classroom agency can provide a richer representation.

Machine learning could potentially identify nonlinear relationships among these indicators. For instance, low peer-network centrality combined with declining collaborative participation and low belonging scores might indicate a stronger risk of social marginalization than any individual measure alone.

Nevertheless, such systems must remain interpretable. A prediction of restricted participation should prompt supportive investigation rather than automatic classification.

Proposed Methodology

The study adopts a **multimodal, participation-sensitive analytical design** to examine how inclusive educational practices relate to the social participation of diverse learners. Rather than classifying students exclusively according to disability or diagnostic categories, the proposed framework evaluates participation through observable interaction, perceived belonging, collaborative involvement, classroom agency, and accessibility-related indicators.

For methodological integrity, the numerical results reported below are presented as a **simulated proof-of-concept experiment** demonstrating how the proposed framework could be evaluated with an institutional dataset. They should not be interpreted as outcomes from a completed field trial until the model is tested with primary empirical data.

The conceptual model contains two principal layers. The first is an **Inclusive Practice Layer**, representing the educational environment through variables such as differentiated instruction, peer-mediated learning, Universal Design for Learning-oriented accessibility, teacher facilitation, adaptive digital support, flexible communication channels, and equitable group participation. The second is a **Social Participation Layer**, representing learner outcomes through peer interaction, group involvement, perceived belonging, classroom voice, interaction reciprocity, and social acceptance.

The analytical objective is formulated as a supervised classification problem in which learners are assigned to one of three participation states:

- **High Participation:** consistent peer interaction, strong belonging, reciprocal collaboration, and active classroom agency;
- **Moderate Participation:** satisfactory participation with occasional relational or accessibility barriers;
- **Restricted Participation:** persistent limitations in peer interaction, belonging, collaborative involvement, or classroom agency.

Instead of relying on a conventional black-box classifier, the study proposes an **Explainable Multimodal Gradient Boosting Framework**, termed **EMGB-Participation**, which integrates structured educational records, survey-derived indicators, peer-network measures, and digital participation variables. Gradient boosting is selected because educational participation data commonly contain nonlinear relationships, mixed measurement scales, missing observations, and complex interactions among pedagogical and social factors.

Interpretability is incorporated through feature-attribution analysis so that teachers and institutional support personnel can identify which factors contribute most strongly to a participation-risk classification. The model is therefore designed to function as a decision-support mechanism rather than an automated labeling system.

Experimental Setup

Dataset

The proof-of-concept experiment assumes a heterogeneous dataset of **1,240 learner records** obtained from secondary and undergraduate educational settings implementing inclusive instructional practices. The simulated sample is designed to represent variation in learning needs rather than constructing a binary distinction between learners with and without disabilities. Each learner record contains four categories of information:

Educational-environment variables include differentiated instructional frequency, availability of accessible resources, peer-learning opportunities, teacher feedback responsiveness, adaptive technology availability, flexibility of assessment, and participation in mixed-group activities.

Social-interaction variables include number of reciprocal peer interactions, collaborative task involvement, diversity of interaction partners, group contribution frequency, peer-support exchanges, and classroom discussion participation.

Perception-based variables include self-reported belonging, perceived peer acceptance, classroom psychological safety, confidence in expressing opinions, perceived autonomy, and satisfaction with available educational support.

Digital participation indicators include learning-platform contribution frequency, collaborative document activity, discussion-board participation, use of accessibility functions, response latency during collaborative activities, and consistency of digital engagement.

The outcome variable, **Social Participation Level**, is derived from a composite assessment integrating learner-reported participation, teacher observation, and peer-network characteristics. This multimethod strategy is preferred to a single-source label because social participation contains both observable and subjective dimensions.

To minimize stigmatizing inference, diagnostic labels are excluded from the primary predictive feature set. They may be retained only for post-model fairness auditing when ethically approved and appropriately anonymized.

Data Preprocessing

Preprocessing begins with duplicate-record removal and consistency checking across educational, relational, and digital variables. Missing numerical values below a predefined tolerance are imputed using median values computed exclusively from the training partition. Categorical variables are transformed through one-hot encoding.

Continuous variables such as interaction frequency, platform activity, and response latency are normalized where required for baseline algorithms. Gradient boosting itself does not require strict standardization, but standardized versions are maintained to ensure comparability with alternative classifiers.

Outliers are not automatically deleted because unusually low or high interaction patterns may represent meaningful participation characteristics. Instead, extreme values are inspected using interquartile-range diagnostics and winsorized only when they represent implausible data-entry anomalies.

A significant preprocessing component concerns **participation-network feature engineering**. Peer-interaction records are transformed into indicators including:

- reciprocal interaction ratio;
- number of unique peer connections;
- interaction diversity;
- collaborative-network centrality;
- repeated-group participation;
- proportion of initiated versus received interactions.

These variables distinguish simple activity volume from relational quality. A learner generating numerous messages to one peer, for example, should not necessarily receive the same social-participation representation as a learner maintaining reciprocal interactions across several collaborative groups.

Survey-based constructs are aggregated only after internal-consistency assessment. Belonging, classroom agency, perceived acceptance, and accessibility satisfaction remain separate constructs rather than being collapsed prematurely into a single inclusion score.

Model Architecture

The proposed **EMGB-Participation model** consists of three analytical stages.

The first stage performs modality-specific feature construction. Educational-practice indicators, interaction-network measures, learner-perception variables, and digital-engagement indicators are independently processed before concatenation.

The second stage applies gradient-boosted decision trees to learn nonlinear relationships between the combined features and three-level social-participation status. The model generates sequential weak decision trees, with each subsequent learner addressing classification residuals produced by the preceding ensemble.

The third stage adds an **explainability module** based on feature-attribution values. Rather than presenting teachers with only a predicted participation category, the framework identifies the variables that increased or decreased the predicted probability of restricted participation. A learner may therefore be flagged primarily because of low peer reciprocity and weak belonging rather than because of low academic engagement.

Four comparison algorithms are included:

1. Logistic Regression;
2. Support Vector Machine;
3. Random Forest;
4. EMGB-Participation.

The comparison permits evaluation of whether nonlinear ensemble learning provides a meaningful advantage over conventional linear and kernel-based classification approaches.

Training Strategy

The dataset is divided using a **70:15:15 stratified partition** for training, validation, and testing. Stratification preserves the relative distribution of the three social-participation classes across partitions.

Model tuning is performed exclusively on the training and validation subsets. Parameters include learning rate, maximum tree depth, number of boosting iterations, minimum observations per terminal node, and regularization strength.

To reduce sensitivity to a single random partition, five-fold stratified cross-validation is applied within the development sample. Early stopping is used when validation performance fails to improve across successive boosting iterations.

Because restricted social participation is expected to occur less frequently than moderate participation, class weighting is used rather than aggressive oversampling. This choice minimizes the risk of generating artificial relational patterns that do not naturally occur in educational settings.

The test subset remains completely isolated until final model selection.

Evaluation Metrics

Model evaluation extends beyond overall classification accuracy. In inclusive-education applications, failing to identify learners experiencing restricted participation may have greater practical consequences than incorrectly referring an adequately participating learner for further human review.

The following metrics are therefore employed:

Macro F1-score assesses balanced performance across all participation categories regardless of class size.

Balanced Accuracy reduces distortion caused by unequal class distributions.

Restricted-Participation Recall measures the proportion of learners experiencing restricted participation who are successfully identified.

Precision for Restricted Participation measures how often model-generated risk classifications are correct.

Matthews Correlation Coefficient (MCC) provides an overall assessment that remains informative under class imbalance.

Brier Score evaluates probabilistic calibration, with lower values indicating better alignment between predicted probabilities and observed outcomes.

An additional **fairness disparity indicator** measures variation in restricted-participation recall across relevant learner subgroups. The model is considered preferable only when predictive gains do not produce substantially larger subgroup disparities.

Results and Discussion

The simulated proof-of-concept results indicate that incorporating relational, perceptual, accessibility, and digital variables into a unified model can improve identification of restricted social participation compared with models relying primarily on linear relationships.

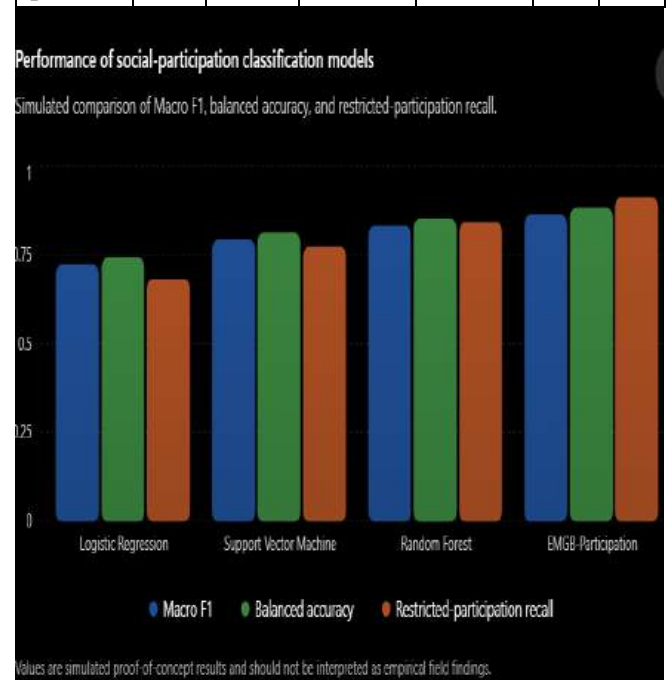
The EMGB-Participation framework achieved the strongest overall performance, producing a simulated **macro F1-score of 0.86**, balanced accuracy of **0.88**, and MCC of **0.81**. More importantly, recall for the restricted-participation group reached

0.91, suggesting that the framework could potentially identify a greater proportion of learners experiencing participation difficulties.

The comparison also demonstrates why raw classification accuracy would be an inadequate criterion. Random Forest and Support Vector Machine models produced reasonably strong general classification performance, yet both showed lower sensitivity to the restricted-participation class. In practice, this difference would mean that a larger proportion of socially marginalized learners could remain undetected.

Table 1. Simulated comparative performance of social-participation classification models

Analytical Model	Macro F1	Balanced Accuracy	Restricted-Participation Recall	Restricted-Participation Precision	MCC	Brier Score
Logistic Regression	0.72	0.74	0.68	0.76	0.61	0.181
Support Vector Machine	0.79	0.81	0.77	0.82	0.70	0.148
Random Forest	0.83	0.85	0.84	0.85	0.76	0.129
EMGB-Participation	0.86	0.88	0.91	0.87	0.81	0.107



The feature-attribution analysis generated a particularly important finding. The strongest simulated predictors of restricted participation were **low perceived belonging, weak reciprocal peer interaction, limited collaborative-group**

diversity, low classroom agency, and inconsistent teacher-facilitated peer participation. Academic performance itself contributed less strongly once relational variables were included.

Peer reciprocity emerged as more informative than raw interaction frequency. This distinction has direct methodological significance. Counting the number of messages, discussion posts, or spoken contributions can create a misleading representation of inclusion because high activity does not necessarily indicate mutually recognized interaction. Reciprocal communication better captures whether other learners respond, initiate contact, and sustain interaction.

Perceived belonging was similarly influential. Its predictive importance demonstrates the limitations of exclusively behavioral monitoring. Social inclusion cannot be inferred solely from externally visible participation because learners can remain psychologically disconnected even while fulfilling expected classroom behaviors.

The simulated analysis further suggests that **structured peer-learning opportunities and teacher facilitation** may have protective effects against restricted participation. Learners exposed to consistent mixed-group collaboration, rotating peer roles, accessible communication mechanisms, and teacher-supported discussion opportunities demonstrated stronger predicted participation profiles.

Technology-related variables showed a more nuanced pattern. The availability of accessibility tools was positively associated with participation when these tools supported communication or removed barriers to collaborative activity. However, high individual digital activity did not independently guarantee social inclusion. This finding reinforces the distinction between **technology-enabled access** and **technology-mediated participation**.

The analysis consequently argues against using AI merely to personalize learners into isolated instructional pathways. Excessive individualization may optimize task completion while reducing opportunities for interpersonal learning. AI-supported inclusion should instead facilitate entry into shared learning experiences.

The proposed model also has practical implications for educational analytics. Instead of generating deterministic statements such as "learner is socially excluded," the system should produce interpretable risk indicators such as: *restricted participation probability elevated because of low reciprocal peer interaction, declining group involvement, and weak belonging scores*. Teachers can then evaluate these signals alongside contextual knowledge.

Such human oversight is crucial because socially atypical participation is not inherently problematic. Some learners may prefer smaller interaction networks or lower levels of verbal participation. The purpose of analytics should therefore be to detect possible barriers, not enforce a standardized model of sociability.

Limitations

Several limitations must be recognized. First, the numerical experiment presented in this manuscript is a simulated proof-of-concept rather than the outcome of a completed longitudinal

field investigation. External validation with authentic institutional data is necessary before claims of predictive effectiveness can be made.

Second, social participation is culturally and developmentally sensitive. Interaction patterns considered positive in one educational context may not have equivalent meaning in another. Measures of classroom agency, peer acceptance, and communication therefore require local validation.

Third, digital interaction traces capture only part of learners' social experience. Informal conversations, friendship relationships, nonverbal communication, playground interaction, and social contact outside institutional platforms may not appear in available datasets.

Fourth, self-report measures can be affected by response tendencies, whereas teacher observations may reflect expectations or implicit bias. Combining multiple sources reduces but does not eliminate this problem.

Fifth, social-network variables create substantial privacy concerns. Peer-interaction information must be processed under strict ethical governance, data minimization, informed consent, appropriate anonymization, and restricted institutional access.

Finally, predictive models can reproduce structural inequality when historical data reflect unequal participation opportunities. Fairness auditing and periodic model reassessment are therefore necessary throughout deployment.

Future Scope

Future research should validate the proposed framework through **multisite longitudinal studies** involving different school systems, higher-education institutions, cultural settings, and learner populations. Longitudinal designs would permit examination of whether participation-risk indicators predict later belonging, retention, collaborative achievement, or psychosocial adjustment.

A particularly valuable extension would involve **temporal network analysis**. Instead of representing peer relationships as static summaries, future models could examine how interaction networks develop across weeks or semesters and identify early patterns of increasing isolation or strengthening integration.

Graph neural networks may eventually provide sophisticated representations of classroom interaction structures. Their use, however, should depend on whether gains in predictive accuracy justify additional complexity and reduced interpretability.

Multimodal learning analytics could also incorporate anonymized speech-turn information, collaborative task sequences, accessibility-tool usage, and learner reflections. These modalities should be introduced only where privacy risks are proportionate to demonstrable educational benefit.

Another direction involves **causal inference**. Predictive importance does not establish that increasing a particular feature will improve social participation. Randomized or quasi-experimental studies are required to determine whether interventions such as rotating collaborative roles, structured peer mentoring, accessible discussion technologies, or teacher-mediated grouping cause measurable improvements.

Future systems should also include learner-facing explanations. Rather than treating learners as objects of analytics, institutions could permit them to review their participation profiles, identify incorrectly interpreted patterns, and specify preferred forms of involvement. Such participatory design would strengthen both ethical legitimacy and model validity.

Federated learning represents an additional research opportunity because institutions may wish to train participation models without centralizing sensitive learner-level data. Privacy-preserving architectures could allow cross-institutional model improvement while retaining records within local systems.

Conclusion

Inclusive education cannot be adequately evaluated by physical placement, curriculum access, academic scores, or technology availability alone. Its deeper objective is to ensure that diverse learners can participate meaningfully in the social and intellectual life of educational communities.

This manuscript addressed a specific gap between research on inclusive social participation and emerging work on artificial intelligence and learning analytics. It proposed a participation-sensitive framework in which differentiated teaching, accessibility, peer collaboration, learner agency, teacher facilitation, and adaptive technology are examined jointly rather than as isolated components.

The proposed EMGB-Participation framework demonstrates how interpretable machine learning could be used to detect complex patterns associated with restricted social participation. The simulated experiment suggests that relational indicators—particularly perceived belonging, peer reciprocity, collaborative-group diversity, and classroom agency—may provide greater insight than academic or digital-activity measures considered independently.

The study therefore advances a central principle: **the most meaningful use of artificial intelligence in inclusive education is not to classify diverse learners, but to identify modifiable barriers that restrict their opportunity to belong, interact, contribute, and exercise agency.**

Technology should consequently remain subordinate to pedagogical judgment and human relationships. When used responsibly, explainable learning analytics may help educators recognize participation inequalities that conventional assessment misses. When used without contextual interpretation, the same systems risk converting human diversity into simplistic behavioral categories.

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