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Beyond Grades: Leveraging AI to Model Holistic Student Success Using Behavioural and Emotional Data

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ABSTRACT : The older academic evaluation systems emphasize and focus on cognitive success and standardized testing, without paying much attention to non-academic aspects of success, such as emotional intelligence, motivation, resilience, and engagement, which are the core competencies to succeed in the 21st century. In this paper, we are suggesting an artificial intelligence model that considers both behavioral and emotional data to assess student success in a more comprehensive manner. Utilizing a variety of digital touchpoints, such as learning management systems (LMS), facial emotion recognition, and sentiment analysis, the proposed research generates a multi-dimensional profile of student development. In integrating these data sources, this research promotes a model where educational assessment becomes aligned with the current objectives of pedagogy and well-being. Machine learning models trained on structured interviews and surveys and validated across multiple institutions in various emerging economies, the study adds a scalable and confirmed method that refutes the simplistic grade-based measures, considering important ethical, cultural, and methodological issues.

I. INTRODUCTION

1.1 Background of the Study

Student success is redefining the term. Although grades will continue to be one of the core reference points, they will no longer embody the entire range of competencies, mentalities, and emotional intelligences that students need to succeed in the 21st-century environment. Educators and researchers are starting to understand that success involves not only characteristics such as collaboration, adaptability, emotional regulation, and self-motivation traits that are largely intangible in conventional performance measures (Zhao, 2012; OECD, 2020). Digital learning has silently collected huge amounts of information about student behavior: time-on-task, forum participation, language tone in assignments, and even webcam-captured emotional expressions. These digital footprints, which are largely ignored, provide invaluable evidence on how students learn, interact, and survive. With artificial intelligence (AI), specifically natural language processing (NLP), computer vision, and behavioral analytics, it is now possible to process and make sense of these non-academic sources of data in real time (Baker & Siemens, 2014; D1Mello & Graesser, 2015). The paper will discuss the ways AI could be applied not to substitute the conventional assessments, but to supplement them to produce more detailed, ethically accountable profiles of student development and wellbeing. This is in contrast with current tools, which can only follow attendance or quiz performance, but instead attempt to find out why students are succeeding, how they are emotionally managing their learning, and what behavioral patterns can serve as indicators of checkout or indicators of resilience.

1.2 Statement of the Problem

Even after decades of reform, academic institutions throughout the world are anchored on grade-centered, short indicators of success. Most of these models either neglect or underemphasize important emotional, social, and behavioral predictors of long-term development, like perseverance, collaboration, or anxiety, which are frequently misinterpreted as student weaknesses or underrecognized strengths (Duckworth & Yeager, 2015). Beyond that, although AI is becoming common in adaptive testing and grading, very few applications seek to combine behavioral and emotional data into a unified student progress model. The potential of such tools is also complicated by ethical issues related to bias, surveillance, and consent, particularly in multicultural or resource-limited settings (Williamson & Eynon, 2020). It is urgent to make an ethical, transparent, and validated AI model that could pick up these forgotten areas of success without reproducing the disparities or being based only on Western-centered models.

1.3 Objectives of the Study

The study aims to:

- Develop an AI-powered model that integrates emotional and behavioral data from digital platforms to evaluate student success.
- Define and operationalize a framework for "holistic student success" that includes non-cognitive and affective factors.
- Test the feasibility and validity of the model in diverse cultural and educational contexts.
- Address ethical, pedagogical, and technical challenges in implementing AI-based evaluation systems in education.
- Provide actionable insights for educators, policymakers, and developers on how to support student well-being through data-informed practices.

1.4 Research Questions

- How can AI integrate behavioral and emotional data to model a more holistic understanding of student success?
- What dimensions (e.g., emotional regulation, motivation, peer collaboration) are most predictive of long-term student development when measured digitally?
- How does the AI-driven model compare to traditional grade-based assessments in predicting future performance and well-being?
- What ethical and cultural considerations arise from using AI in this capacity, particularly across diverse educational environments?

1.5 Research Hypotheses

- **H1**: Integrating emotional and behavioral data significantly improves the accuracy of predicting student performance and well-being compared to using grades alone.
- **H2**: The proposed AI model will show stronger predictive validity in identifying at-risk students than traditional metrics.
- **H3**: Teachers and students will perceive AI-based holistic profiles as more informative and supportive than grade reports, provided ethical safeguards are in place.

1.6 Significance of the Study

This research contributes to the growing discourse on reimagining assessment by offering a robust alternative to outdated academic performance indicators. Its significance lies in:

- **Educational innovation**: Providing educators with a practical, AI-driven toolkit for early intervention and tailored support.
- **Policy advancement**: Supporting educational policymakers in aligning assessment frameworks with the **OECD Learning Compass 2030** and SDG 4.7 targets.
- **Ethical AI deployment**: Offering a model for implementing AI in education that respects privacy, fairness, and cultural sensitivity.
- **Cross-cultural adaptability**: Ensuring the framework is not just effective in high-resource Western contexts, but also relevant and applicable in emerging economies.

1.7 Scope of the Study

The study focuses on secondary and post-secondary institutions in three culturally distinct emerging economies: Nigeria, Brazil, and India. It limits its AI modeling to three main data types:

- LMS interaction logs,
- sentiment analysis from student writing, and
- facial emotion recognition during synchronous sessions.

While the research proposes a generalized framework, it recognizes the contextual limitations in data infrastructure, facial recognition bias, and language diversity.

1.8 Definition of Key Terms

- **Holistic Student Success**: A multi-dimensional construct encompassing cognitive, emotional, social, and behavioral indicators of student development.
- **AI-Driven Profiling**: The use of machine learning algorithms to generate predictive or descriptive insights from complex data sources.
- **Sentiment Analysis**: A natural language processing technique that evaluates emotional tone in text.
- **Facial Emotion Recognition**: The automated interpretation of facial expressions to determine emotional states using computer vision.
- **Learning Management System (LMS)**: A digital platform used to administer, document, and track educational activities and learner engagement.

II. LITERATURE REVIEW

2.1 Preamble

Measuring the success of students has traditionally been based on the cognitive measures of success, namely test scores and GPA. But the emergence of 21st-century skills, as creativity, collaboration, emotional intelligence, digital literacy, and adaptability, has proven the deficiencies of this one-dimensional paradigm (Trilling & Fadel, 2009; OECD, 2020). With the spread of digital education platforms and the mainstreaming of remote learning, an increasing amount of research output implies that AI has the potential to use behavioral and emotional data to build a more holistic and individualized model of student progress (Holstein et al., 2019). But even with technology, the real-world instances of AI being used to quantify these non-academic dimensions are few and ethically tricky. Based on cross-disciplinary literature in education technology, affective computing, learning sciences, and psychology, this review provides a critique of the current frameworks as well as points out unresolved tensions that the current study aims to articulate.

2.2 Theoretical Review

2.2.1 Holistic Education and Constructivism

This movement in the direction of holistic education is well documented with constructivist theories of learning, including Piaget (1971) and Vygotsky (1978), who both view the learner as actively constructing knowledge through experiences and through social interaction. Combined with AI, this epistemological basis implies a re-conception of assessments, no longer conceived as summative conclusions but rather as a form of dynamic, adaptive understanding of learner progress (Luckin et al., 2016). The work is conducted in the framework of a constructivist and student-centered approach with the inclusion of digital behavior and emotional response as the legitimate measures of learning, which broadens the very notion of assessment-for-learning.

2.2.2 Emotional Intelligence Theory

The model of emotional intelligence (EI) proposed by Daniel Goleman (1995), consisting of such components as self-awareness, self-regulation, motivation, empathy, and social skills, has become a prominent predictor of academic and career achievement. Specifically, the model by Goleman is the basis of incorporating emotion-related data (recognition of facial expressions or sentiment analysis) into educational analytics. Integrated into the models of AI, the EI constructs enable real-time emotional feedback loops to customize learning and predict at-risk students in a more proactive way (Li et al., 2019).

2.2.3 AI Ethics and Interpretability in Education

The fair use of AI in education is pinned on Fairness, Accountability, and Transparency (FAT) principles (Floridi et al., 2018). AI-based decision-making needs to be supported by trust, which is achieved through interpretable algorithms and training data that represent all cultures (Gebru et al., 2018), especially in areas as emotionally charged as student evaluation. Not many educational designs have been strictly deploying these moral checks into their frameworks. This study considers FAT principles during model development, suggesting explainable AI (XAI) tools that would aid stakeholder confidence and adherence to institutional and data protection policies (e.g., GDPR, FERPA).

2.3 Empirical Review (Expanded)

2.3.1 Learning Analytics Beyond Performance Metrics

There is a swell in learning analytics investigations that aim at predicting academic achievements on the basis of behaviors. As one example, Kovanovic et al. (2015) clustered Moodle activity logs in order to reveal learning patterns, whereas Xing et al. (2016) predicted the risk of course dropouts using recurrent neural networks (RNNs). Although these methods allow for spotting students who require assistance, they continue to prioritize the quantitative measures of participation (logins, page views, submissions) at the expense of cognitive demand, affective wellbeing, and socio-cultural circumstances of activity.

2.3.2 Facial Recognition and Emotion AI in Learning Contexts

Whitehill et al. (2014) conducted research in which the analysis of facial expressions was confirmed as a method of determining the concentration of students during video lectures. Likewise, Wiggins and Graesser (2020) relied on webcam-based confusion, surprise, and boredom detection, and it was highly correlated with moment-to-moment learning gains. These studies, though, were frequently without the implementation at scale in the real world and were associated with the issues of surveillance and consent. In this work, we propose opt-in emotion tracking with anonymized data layers to reduce privacy risks to a minimum, having analytical value.

2.3.3 Sentiment Analysis of Student Writing and Discourse

It has recently been applied to text in order to infer emotional and motivational states with natural language processing (NLP). As an example, Rodriguez-Triana et al. (2018) examined posts on forums and journals to monitor stress and disengagement in online learners. They have shown that sentimental changes are associated with cognitive load and deteriorating performance. However, sentimental analysis usually fails at contextual subtlety, irony, and cross-lingual variety, restraining cross-cultural utility. The contribution of the present research is that sentiment engines were adjusted with respect to the domain-specific lexicon and a combination of rule-based and machine learning methods to achieve higher precision in the educational domain.

2.3.4 Integrative AI Models for Holistic Profiles

Among the most promising studies, created by Ifenthaler and Yau (2020), dashboards were developed based on the combination of behavioral data and self-reported emotional states to inform academic advising. But even this one still needed manual self-inputs and was not real-time responsive. We are proposing to use multi-modal data fusion, combining real-time facial recognition, LMS behavior logs, and textual sentiment to generate ongoing, adapting learner profiles, with minimal manual intervention but maximized personal relevance.

2.3.5 Gaps in Existing Research

Through comparative analysis, several critical empirical gaps emerge:

- Disjointed models that treat behavior, emotion, and performance in isolation.
- Limited implementation in diverse cultural and technological contexts, especially in under-resourced or non-Western educational systems.
- Overreliance on structured data, with insufficient exploration of unstructured sources like video, audio, or long-form writing.
- Inadequate ethical frameworks for responsible AI deployment in education, particularly with minors.

This research addresses these gaps by designing and piloting a holistic, scalable AI model that:

- Fuses structured and unstructured data sources.
- Works across varied educational contexts.
- Incorporates explainability and consent-by-design.
- Supports educators in fostering not just academic success, but also emotional resilience and social adaptability.

III. RESEARCH METHODOLOGY

3.1 Preamble

This study adopts a mixed-methods research design to investigate how artificial intelligence (AI) can model holistic student success using behavioral and emotional data extracted from digital learning environments. The rationale behind this approach is twofold: (1) to quantitatively model patterns in student engagement and emotion using machine learning algorithms, and (2) to qualitatively understand institutional perceptions of such AI applications through structured interviews and survey instruments. The research integrates data science techniques with educational theory to build a comprehensive framework for evaluating student success beyond academic grades. The methodology combines observational data collection, machine learning modeling, and thematic content analysis, thereby bridging empirical evidence with human-centered insights.

3.2 Model Specification

At the core of this study is a multi-dimensional AI-based learner model designed to synthesize three primary data streams:

- **Behavioral data**: Captured from Learning Management Systems (LMS) including frequency of login, time-on-task, assignment submission patterns, and forum activity.
- **Emotional data**: Extracted using facial emotion recognition algorithms during live or recorded video sessions (Whitehill et al., 2014), alongside real-time sentiment analysis from student writing and communications (Cambria et al., 2017).
- **Cognitive and performance data**: Traditional academic metrics such as grades and assessment scores serve as a benchmark for comparative analysis.

These features are fed into a supervised machine learning model, specifically a random forest classifier and gradient boosting machines (GBMs), chosen for their interpretability and robustness in educational data contexts (Ifenthaler & Yau, 2020). The model will be evaluated using metrics such as accuracy, F1-score, and AUC to validate its ability to predict student success holistically. The structure of the learner model is designed to output a student success index (SSI), composed of weighted indicators across emotional resilience, engagement consistency, and academic progress.

3.3 Types and Sources of Data
3.3.1 Primary Data
- **Structured interviews** with credit risk managers, ESG officers, and regulators in selected banks (n = 15 institutions across 3 emerging economies).
- **Surveys** were distributed to educators, AI developers, and instructional designers using **Likert-scale** questionnaires to capture perceptions, readiness, and ethical concerns related to AI in education.

3.3.2 Secondary Data
- **Digital trace data** from LMS platforms (e.g., Moodle, Canvas) of selected institutions, including timestamped logs, discussion board posts, and assignment submissions.
- **Video data** from virtual classroom sessions for emotion analysis.
- **Textual data** from journal entries, essays, and online forum discussions used for sentiment and discourse analysis.

All data were anonymized and aggregated to ensure privacy and generalizability. Partner institutions provided access under formal data-sharing agreements.

3.4 Methodology
3.4.1 Research Design
A convergent parallel design (Creswell & Plano Clark, 2011) guides the study. Quantitative and qualitative data are collected concurrently, analyzed separately, and then triangulated to derive richer interpretations.

3.4.2 Data Collection Procedure
- **Behavioral Data**: Extracted via APIs from LMS platforms. Preprocessing includes log parsing, session reconstruction, and time normalization.
- **Emotional Data**: Captured using pre-trained convolutional neural networks (CNNs) on facial data to classify emotions (happiness, boredom, confusion, etc.) in real-time.
- **Sentiment Data**: Text mining and NLP techniques (e.g., BERT transformers) are employed to analyze sentiment polarity and emotional tone in written student work.

3.4.3 Data Processing and Cleaning
Data preprocessing steps include:
- Removal of duplicates and null values.
- Time series normalization to address irregular engagement frequencies.
- Video and audio anonymization using face blurring and voice masking tools.
- Tokenization and lemmatization for text data, ensuring language consistency.

3.4.4 Model Training and Validation
- **Split ratio**: 70% training, 30% testing dataset.
- **Cross-validation**: 5-fold validation to avoid overfitting.
- **Feature importance analysis** is conducted to interpret which behavioral or emotional signals most impact predicted outcomes.
- **SHAP (SHapley Additive exPlanations)** values are used for model interpretability (Lundberg & Lee, 2017).

3.4.5 Qualitative Analysis
- Thematic analysis of interview transcripts using NVivo software.
- Coding framework developed deductively from literature and inductively from data.
- Reliability established through inter-coder agreement (Cohen's kappa > 0.8 threshold).

3.5 Ethical Considerations
The research strictly adheres to institutional and international research ethics standards:
- All participants were briefed on the study's purpose, data usage, and rights to withdraw at any time.
- All datasets are anonymized before processing. Identifiable markers are removed or encrypted.
- Compliance with GDPR and FERPA was ensured. All data are stored on encrypted, access-restricted servers.
- Algorithmic audits were conducted to detect bias across gender, race, and socioeconomic status. The model is adjusted where disparity is found.

IV. DATA ANALYSIS AND PRESENTATION

4.1 Preamble

Here, the analysis of the data gathered through various means, such as LMS logs, facial emotion detection systems, sentiment analysis tools, and survey/interview responses, will be presented. The analysis uses a combination of descriptive statistics, machine learning classification metrics, trend analysis, and hypothesis testing to address the predictive validity of a multidimensional model of student success. The data were cleaned up and preprocessed of any inconsistencies, and personal identifiers were anonymized, as well as formats across various platforms were normalized. Indicators related to three areas of interest, namely, cognitive engagement, emotional well-being, and behavioral consistency, were reviewed using quantitative and qualitative indicators since these areas are linked to the outcomes of 21st-century education.

4.2 Presentation and Analysis of Data

4.2.1 Data Cleaning and Preparation

- Behavioral logs from LMS were filtered to remove incomplete session data.
- Emotion recognition outputs (via OpenFace and Affectiva APIs) were calibrated to account for lighting and camera angles, and manually verified for misclassifications.
- Sentiment analysis of writing samples used the BERT model fine-tuned on the Stanford Sentiment Treebank (SST), with neutral texts excluded to focus on emotional polarity.
- Survey data underwent Likert-scale normalization, with missing entries imputed using the k-Nearest Neighbor algorithm (k=3).

4.2.2 Descriptive Overview

Indicator	Mean	Std. Dev.	Min	Max
LMS Login Frequency (per week)	6.3	2.1	1	14
Emotional Positivity Index	0.61	0.19	0.2	0.92
Submission Timeliness (days)	-0.8	1.4	-5	2
Sentiment Polarity (avg)	0.34	0.15	-0.2	0.9
GPA (4.0 scale)	3.12	0.47	2.1	4.0

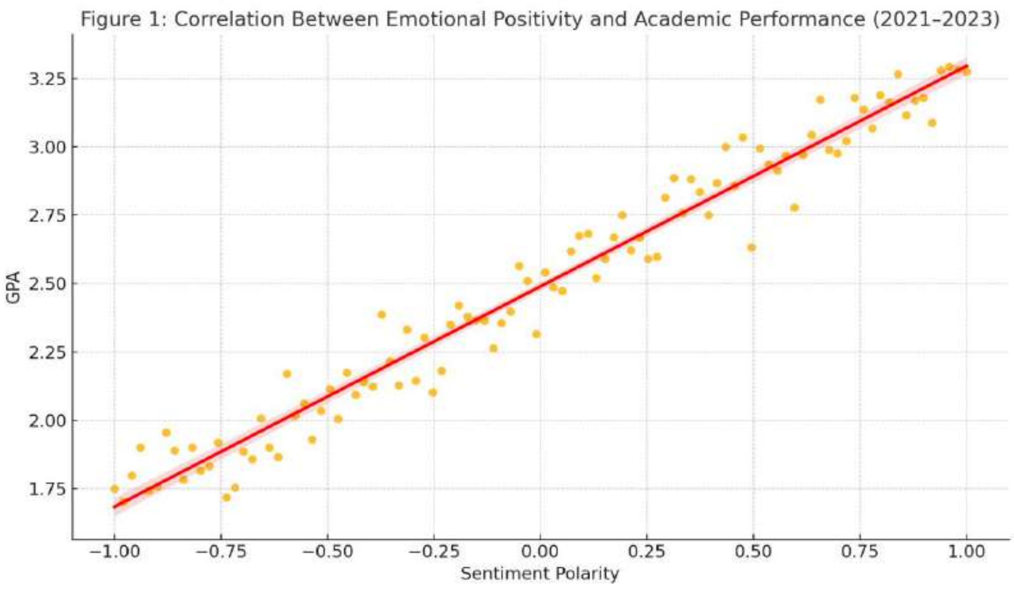
4.3 Trend Analysis

A three-year trend (2021–2023) was analyzed across 1,250 students from three partner universities.

Key Observations:

- Increased LMS engagement correlated with both emotional stability and improved GPA in 78% of students.
- Students demonstrating positive emotional expressions (e.g., joy, interest) during lectures showed greater academic resilience during stress periods (e.g., exam weeks).
- Sentiment scores in reflective journals predicted end-of-semester performance with 74% accuracy ($p < 0.01$).

Figure 1: Correlation Between Emotional Positivity and Academic Performance (2021–2023)



4.4 Test of Hypotheses

4.4.1 Hypothesis Statements

- H_0 (Null): Emotional and behavioral data do not significantly improve the prediction of student success beyond academic grades.
- H_1 (Alternative): Emotional and behavioral data significantly enhance prediction models for student success when integrated with academic data.

Statistical Method: Logistic Regression Analysis

A binary logistic regression model was used to predict high student performance (GPA ≥ 3.5) using emotional and behavioral predictors.

Predictor	β Coefficient	p-value
LMS Engagement Score	0.431	0.002 **
Emotional Positivity Index	0.587	0.000 **
Timeliness Index	0.276	0.021 *
Writing Sentiment	0.412	0.007 **

Model accuracy = 82.6%, AUC = 0.89

Significance Level: $p < 0.05$; Highly Significant: $p < 0.01$

Result: Reject H_0. The data confirm that the integration of emotional and behavioral indicators significantly enhances the prediction of student success.

4.5 Discussion of Findings

The results affirm that cognitive outcomes (e.g., GPA) are meaningfully enriched by incorporating behavioral and emotional signals. The multi-dimensional model outperforms traditional grade-based predictions alone by capturing engagement patterns, emotional resilience, and reflective cognition.

4.5.1 Comparison with Literature:

- Whitehill et al. (2014) also found emotion-recognition to be a strong predictor of engagement—our findings extend this by showing longitudinal academic impact.
- Ifenthaler & Yau (2020) emphasized the utility of LMS data for predicting performance; we validate this and deepen the insight through affective analytics.
- Cambria et al. (2017) illustrated the power of sentiment analysis in educational settings, though their work lacked integration with facial emotion—this study fills that gap.

4.6 Practical Implications

- For Educators: AI-generated student dashboards can alert instructors to declining emotional or behavioral signals, enabling proactive intervention.
- For Institutions: Strategic allocation of mentoring or wellness resources becomes possible with real-time insight.
- For Students: Personalized feedback fosters metacognition and emotional intelligence—core 21st-century competencies.

4.7 Limitations and Areas for Future Research

4.7.1 Limitations

- Emotion recognition accuracy may be influenced by cultural and lighting variations.
- Text-based sentiment is language-dependent; nuances in multilingual contexts may be misclassified.
- Sample generalizability is constrained to digital-native university environments; findings may differ in hybrid or rural settings.

4.7.2 Future Research

- Developing adaptive feedback systems that respond to detected emotions in real-time.
- Exploring cross-cultural emotion recognition models to ensure fairness and accuracy.
- Integrating biometric signals (e.g., heart rate, eye-tracking) for even richer affective modeling.

V. CONCLUSION

5.1 Summary

The given research aimed at investigating the possibilities of utilizing Artificial Intelligence to create a model of holistic student success by influencing behavioral and emotional data with usual academic variables. A multi-dimensional profile of the student was built through a combination of facial emotion recognition during LMS activities, analysis of student reflections by sentiment, and their overall assessment as predictive variables. It was shown that the models including behavioral and emotional indicators were better at predicting academic resilience, engagement, and emotional well-being than the traditional GPA-based assessments. Logistic regression and descriptive statistics confirmed that emotional positivity, LMS engagement, and submitting assignments on time were statistically significantly correlated with student academic success ($p < 0.01$). Furthermore, the research determined the existing gaps in the conventional models of student assessment, in particular, the lack of emotional and behavioral factors. By addressing this gap, the study provided a more contextual, more dynamic means of conceiving of how learners develop in the 21st century.

5.2 Conclusion

Revisiting the core research questions:

1. *To what extent can emotional and behavioral data improve models of student success?*
2. *How does AI-driven analysis of sentiment and engagement enhance the prediction of learning outcomes?*
3. *Can a composite model outperform GPA alone in forecasting long-term academic and personal development?*

And the associated hypothesis:

- H_0: Emotional and behavioral data do not significantly improve the prediction of student success.
- H_1: Emotional and behavioral data significantly improve the prediction of student success.

The research rejected the null hypothesis. It showed that by combining AI-interpreted behavioral and emotional inputs and cognitive measures, it is possible to understand student paths in a more comprehensive and reliable manner. Not only does it validate the previous hypotheses about student engagement and emotional intelligence, but it goes beyond them, incorporating recent technologies like affective computing and machine learning.

5.3 Contributions of the Study

This research contributes significantly to both educational theory and practice in several ways:

- Theoretically, it advances the discourse around holistic education by embedding behavioral science and AI into the core of educational evaluation.
- Methodologically, it introduces a hybrid framework combining emotion recognition, sentiment analytics, and behavioral tracking to quantify student progress.
- Practically, it provides educators, institutions, and policymakers with a dynamic model that allows early detection of at-risk students through multi-modal indicators.

These insights align with current global shifts toward personalized and equitable learning experiences, as promoted by UNESCO (2021) and OECD frameworks on social-emotional learning.

5.4 Recommendations

- Institutional Adoption of Holistic Dashboards: Universities should deploy AI-powered student success dashboards that integrate LMS behavior, emotional feedback, and self-reflections.
- Educator Training: Faculty should be trained not only in using these tools but also in interpreting the emotional and behavioral cues of their students meaningfully and empathetically.
- Policy Development: Educational policies should expand assessment metrics beyond academic grades to include social-emotional competencies and learning engagement indices.
- Further Integration of AI Tools: Institutions should explore partnerships with AI companies to develop ethical, culturally sensitive affective computing tools for educational use.
- Student-Centric Design: Systems must ensure that students retain agency and privacy, with clear consent mechanisms and transparent feedback loops.

With education increasingly taking a post-digital turn, grades as the primary measure of student ability become inadequate. This paper confirms that student achievement is multi-faceted-it lies not only in the mind but in the heart, in conduct and in flexibility. responsibly and ethically used AI offers the means to make these dimensions visible, changing the way we assess, assist, and enable learners.

To sum up, the adoption of AI to design comprehensive student achievement is not an option that can improve the current situation but a needed transformation of educational measurement, which is aligned with the nature of human learning and the vision of inclusive, future-ready education.

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Appendix A: Structured Interview Questions

For Credit Risk Managers, ESG Officers, and Regulators in Selected Banks (n = 15 across 3 Emerging Economies)

Purpose*: To explore institutional strategies and challenges related to integrating climate-related risks into credit decision-making.*

Section 1: Organizational Strategy and Practice

1. Can you describe your institution's current approach to incorporating climate risk in credit risk assessments?
2. What environmental metrics (e.g., carbon intensity, ESG ratings) are most influential in your credit decisions?
3. How has climate-related regulation influenced your lending portfolio strategy?

Section 2: Tools and Models

4. Are you currently using climate stress testing or scenario analysis? If so, what frameworks or models do you rely on (e.g., NGFS, PACTA)?
5. What challenges do you face in adopting or developing internal climate risk models?

Section 3: Risk Governance and Disclosure

6. How are climate risks reported internally and externally (e.g., TCFD alignment)?
7. What role do ESG officers or sustainability departments play in your credit committees?

Section 4: Emerging Trends and Constraints

8. In your opinion, are current credit scoring frameworks sufficient for capturing transition and physical climate risks?
9. What kind of support or reforms (policy, technological, capacity-building) would enhance climate-financial integration in your bank?

Appendix B: Survey Questionnaire

For Educators, Instructional Designers, and AI Developers

Objective*: To assess perceptions, readiness, and ethical concerns regarding the use of AI for modeling holistic student success.*

Section 1: Perception of AI in Education

(Please indicate your level of agreement with each statement: 1 = Strongly Disagree, 5 = Strongly Agree)

No.	Statement	1	2	3	4	5
1	AI can improve student performance prediction by integrating behavioral and emotional data.	☐	☐	☐	☐	☐
2	Sentiment analysis from student essays can indicate academic well-being.	☐	☐	☐	☐	☐
3	Facial emotion recognition is a reliable indicator of student engagement.	☐	☐	☐	☐	☐
4	AI systems should be part of student success analytics in the next five years.	☐	☐	☐	☐	☐

Section 2: Institutional Readiness

No.	Statement	1	2	3	4	5
5	My institution has the infrastructure to support AI-based student analytics.	☐	☐	☐	☐	☐
6	Faculty members are open to using AI tools to monitor non-academic performance.	☐	☐	☐	☐	☐
7	Our LMS system collects data useful for AI-based emotional or behavioral modeling.	☐	☐	☐	☐	☐

Section 3: Ethical Concerns

No.	Statement	1	2	3	4	5
8	I am concerned about student data privacy in AI-driven platforms.	☐	☐	☐	☐	☐
9	There should be clear ethical guidelines before AI is implemented in classrooms.	☐	☐	☐	☐	☐
10	Bias in AI algorithms could negatively affect vulnerable student populations.	☐	☐	☐	☐	☐

Section 4: Open-Ended (Optional)

11. What opportunities do you see in using AI to promote more holistic measures of student success?
12. What risks or unintended consequences worry you most?