

An AI-Linked Global Framework for a Self-Sustainable Engineering Education System

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Abstract

Education forms the foundation for a nation's development. In today's technology-driven era, educators are innovating to enhance learning methodologies. Integrating with Artificial Intelligence (AI), a globally adaptive education framework can facilitate self-sustainable education models that align with global dynamics. This study analyzes students' adaptability in online learning environments across government and non-government institutions, employing four deep learning algorithms to assess adaptability factors. Performance comparisons showed that the Random Forest Classifier achieved the highest accuracy at 87%, followed by Support Vector Classifier at 84%. Additionally, this research proposes an AI-enhanced education model to foster self-sustainable engineering education, ensuring equitable learning opportunities worldwide.

Keywords: AI in education, self-sustainable learning, online learning adaptability, deep learning models, education framework.

1. Introduction

Education aims to impart knowledge that fosters intellectual growth and employment opportunities. However, modern education systems often emphasize examination-oriented learning over creativity and innovation. This research investigates students' adaptability to online learning and proposes an AI-driven self-sustainable education framework that ensures equitable access to quality education across different geographies.

Key research objectives include:

- Developing a globally applicable education model for equal knowledge dissemination.
- Encouraging entrepreneurship through education.
- Identifying gaps in current learning methodologies and proposing AI-driven solutions.

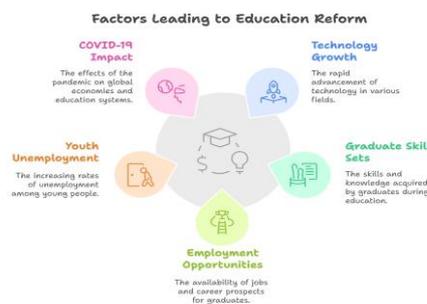


Figure 1: Factors Leading to Education Reform

Graduates' skill sets must evolve in tandem with technological advancements [Reviewer Comment: Consider rephrasing for clarity, e.g., 'Graduates' skill sets must evolve in tandem with technological advancements.'], leading to better employment opportunities. However, this is not the case. As illustrated in Figure 1, youth unemployment rates have shown a persistent increase over the years, particularly peaking around 2020. This reflects the gap between educational outcomes and job market demands. The global unemployment surge in 2020, largely due to the COVID-19 pandemic, further emphasizes the urgent need for a reformed, skill-oriented education model that enhances employability.

2. Literature Review

The COVID-19 pandemic highlighted challenges in education, such as limited access to research facilities, disrupted learning schedules, and increased reliance on digital platforms (Oneyama et al., 2020). Studies indicate the need for digital infrastructure, government intervention, and innovative AI-powered solutions to bridge learning gaps (Murphy, 2020; Teras et al., 2020).

A significant challenge in implementing effective online learning is addressing various barriers that hinder student engagement and adaptability. Figure 2 illustrates key challenges in online learning and how resolving them contributes to **Enhanced Online Learning**:

- **Digital Tool Proficiency:** Ensuring students and educators have adequate training in online learning platforms.
- **Internet Accessibility:** Bridging digital divides by improving connectivity, especially in rural areas.
- **Student Engagement:** Implementing interactive learning techniques and AI-based adaptive learning.
- **Device Constraints:** Providing access to affordable and compatible learning devices.

By addressing these challenges, institutions can foster an inclusive and **highly effective online education system**.



Figure 2: Overcoming Online Learning challenges

While existing frameworks focus on access and digital infrastructure, few integrate AI analytics with institutional collaboration and entrepreneurial development. This study bridges that gap by proposing a triadic model addressing adaptability, infrastructure, and innovation.

3. Methodology

This study employs a data-driven approach to evaluate online learning adaptability using four machine learning algorithms: **Support Vector Classifier (SVC)**, **Logistic Regression**, **K-Nearest Neighbors**, and **Random Forest Classifier**. The *dataset* consisted of 675 student responses from six institutions, including 60% undergraduates and 40% postgraduates, spanning five regions, considering variables such as educational background, internet access, and engagement levels.

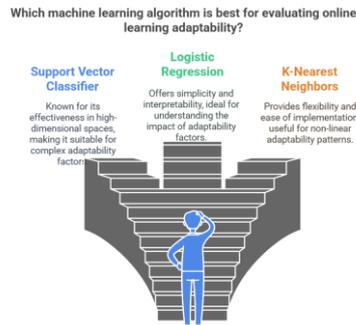


Figure 3: Online learning adaptability

As illustrated in Figure 3, the choice of a machine learning algorithm depends on the complexity of the data and the need for interpretability.

- If the goal is deeper adaptability insights, Logistic Regression may be preferable.
- For complex student behavior modeling, Support Vector Classifier is better.
- For flexible, non-linear adaptability modeling, **KNN** is a strong choice.

3.1 Data Collection & Processing

- **Primary Data Sources:** Student surveys, university databases.
- **Secondary Data Sources:** Published research articles, online learning analytics.
- **Sampling Technique:** Stratified random sampling to ensure diverse representation.

3.2 Analytical Methods

- **Performance Metrics:** Accuracy, recall, precision, and F1-score.
- **Classification:** Adaptability was categorized into three groups (low, moderate, high) based on machine learning predictions.
- **Visualization:** Confusion matrices and feature importance rankings were generated for result interpretation.

4. Results & Discussion

As illustrated in Figure 4, five critical factors influence a student's ability to adapt to online learning environments:

Institutional Support: Educational institutions are crucial in providing resources, faculty training, and student support programs that enhance adaptability.

Internet Accessibility: Stable and high-speed internet access is essential for students to participate in online learning fully.

Previous Exposure to E-Learning Tools: Students familiar with digital learning platforms adapt faster to online education systems.

Socioeconomic Background: Financial constraints, access to personal devices, and family support impact students' ability to engage effectively in online learning.

Course Duration and Engagement Levels: Well-structured courses with interactive elements improve adaptability by maintaining student interest and motivation.

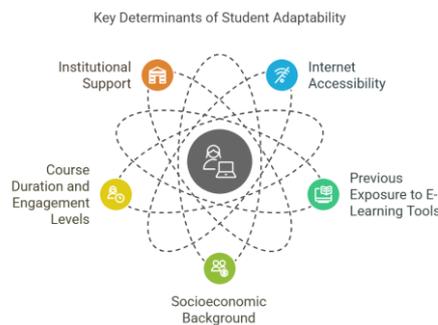


Figure 4: Students Adaptability

Recognizing and addressing these factors can **enhance online learning experiences**, making digital education more accessible and effective for diverse student populations.

The study highlights that adaptability is highest among students aged **21–25**, while individuals over **27** face greater challenges in adjusting to digital learning environments.

4.1 Implications for Education Policy

Figure 5 illustrates a multi-layered approach to improving education using AI-driven solutions and infrastructure enhancements. The descending layered structure represents a systematic transformation in education through four key components:

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	78%	0.77	0.75	0.76

Support Vector Classifier	84%	0.83	0.81	0.82
KNN	76%	0.74	0.72	0.73
Random Forest	87%	0.86	0.85	0.85

Table 1: Performance comparison

Customized Learning Plans (Top Layer - Blue)

- AI-powered personalized learning paths tailored to individual student needs.
- Ensures adaptive learning experiences based on student performance and engagement.

Infrastructure Development (Green Layer)

- Investments in digital infrastructure, high-speed internet, and accessible technology for students.
- Essential for bridging the digital divide and enabling seamless online learning.

Teacher Training (Green Layer)

- Focuses on equipping educators with AI-integrated teaching methodologies.
- Ensures teachers can effectively use digital tools and adaptive learning technologies.

Entrepreneurial Education (Bottom Layer - Yellow)

- Encourages students to develop business and problem-solving skills.
- Integrates real-world projects to foster innovation and entrepreneurship within education.

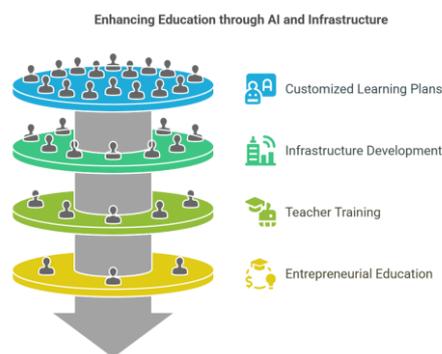


Figure 5: Education Enhancements using AI

The downward flow signifies how these components collectively enhance the education system, making it more adaptive, accessible, and innovation-driven.

4.2 Limitations & Future Research

Expand Data Scope: Current research primarily focuses on university-level students. Future studies should include school-level data.

Optimize AI Models: Advanced techniques such as deep learning and ensemble models could enhance classification.

Explore Cultural Differences: Incorporate socio-economic and regional diversity to improve generalizability.

Address AI Ethics: Include data privacy, algorithmic bias, and ethical AI deployment in education.

While this study provides critical insights, certain limitations exist:

Expand Data Scope: Current research primarily focuses on university-level students. Future studies should include **school-level data** to provide a more comprehensive understanding of adaptability across different age groups.

Optimize AI Models: Refinement of the **machine learning algorithms** used in the study can improve predictive accuracy. Advanced AI techniques such as **deep learning and ensemble models** could enhance adaptability classification.

Explore Cultural Differences: Learning adaptability varies across **geographies, socio-economic backgrounds, and cultural contexts**. Incorporating these factors would enhance the **generalizability of the proposed AI-driven education model**.

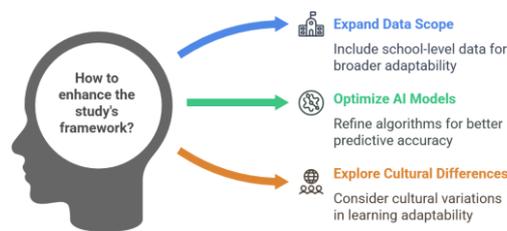


Figure 6: Study Framework

Figure 6 illustrates these key enhancements that can strengthen the study’s framework and improve its applicability in real-world education systems.

As a next step, a pilot deployment is being considered across two institutions in India and South Africa to assess model feasibility and impact on course completion rates.

5. Proposed AI-Driven Education Model

To create a self-sustainable educational system, a triadic approach is introduced [Reviewer Comment: You might consider simplifying this to 'a triadic approach is introduced' for academic tone.], as illustrated in

Figure 7. This approach integrates AI-based learning analytics, institutional collaboration, and entrepreneurial development to transform education:

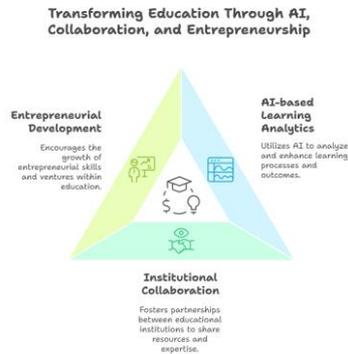


Figure 7: AI-based Learning Analytics

This visual represents how analytics, collaboration, and entrepreneurship integrate to reshape global education models.

AI-Based Learning Analytics

- AI analyzes student performance, predicts learning outcomes, and personalizes educational content.
- AI-driven insights enable educators to develop adaptive learning models tailored to individual student needs.

Institutional Collaboration

- Establishing strong partnerships between educational institutions fosters knowledge sharing, resource pooling, and research collaboration.
- Institutions can implement best practices and work together to create a unified global learning framework.

Entrepreneurial Development

- Encouraging students to develop entrepreneurial skills within their educational institutions promotes real-world problem-solving.
- Universities and colleges can incorporate business incubation **programs** to support student-led ventures.

This model shifts education from a **passive consumption approach** to an **active knowledge creation process**, ensuring long-term sustainability and economic impact.

6. Conclusion

This research underscores the necessity of AI-integrated, self-sustainable education models to enhance online learning adaptability. By leveraging AI-based analytics, institutions can develop **data-driven policies** that support **personalized learning experiences, infrastructure enhancements, and entrepreneurial education programs**.

A globally unified **AI-powered education framework** can **bridge socio-economic disparities, create equal learning opportunities, and foster innovation-driven career paths**. Future research should focus on refining AI-based models and assessing their impact across diverse educational settings.

References:

1. Edeh Michael Onyema, Nwafor Chika Eucheria, Faith Ayobamidele Obafemi, Shuvro Sen, Fyनेface Grace Atonye, Aabha Sharma, Alhuseen Omar Alsayed. “Impact of Coronavirus pandemic on education.”, Journal of Education and Practice. Vol 11, No 13, pp:108-120, 2020.
2. Murphy MP. COVID-19 and emergency eLearning: Consequences of the securitization of higher education for post-pandemic pedagogy. Contemporary Security Policy. 2;41(3), pp 492-505,2020
3. Teras.M, Suoranta, J, Hanna T, Mark C, Post-Covid-19 Education and Education Technology ‘Solutionism’: a Seller’s Market. Post digital Sci Education 2, pp: 863-878,2020.
4. Sobaih, A.E.E.; Hasanein, A.M.; Abu Elnasr, A.E. Responses to COVID-19 in Higher Education: Social Media Usage for Sustaining Formal Academic Communication in Developing Countries. Sustainability, 12, 6520
5. Pravat Kumar Jena, Impact of pandemic covid-19 on education in India, International Journal of Current Research. 2020; 12(7) :12582-12586.
6. Lokanath Mishra, Tushar Gupta and Abha Shree. Online teaching-learning in higher education during lockdown period of COVID-19 pandemic. International Journal of Educational Research Open, 10th Sept., 2020.
7. Abdulrahman Essa Al Lily,. Abdulrahim Fathy Ismail, Fathi Mohammed Abunasser, Rafdan Hassan Alhajhoj Alqahtani “Distance education as a response to pandemics: Coronavirus and Arab culture.” Technology in society vol. 63 (2020): 101317. doi: 10.1016/j.techsoc.2020.101317
8. Laura Engel, Heidi Gibson & Kayla Gatalica. Global Education in Context: Four Models, Four Lessons, Education week, January 18, 2019
9. Shazia Rashid and Sunishtha Singh Yadav. Impact of covid-19 pandemic on higher education and research, Indian Journal of Human Development, Institute for Human Development; pp. 1-4, 2020.
10. Blandford RD, Thorne KS. Post-pandemic science and education. American Journal of Physics.;88(7):518-20, 2020
11. <https://www.statista.com/statistics/812106/youth-unemployment-rate-in-india/>
12. https://www.ilo.org/asia/media-centre/news/WCMS_737997/lang--en/index.htm
13. A report by world economic forum “Schools of the Future Defining New Models of Education for the Fourth Industrial Revolution” Jan 2020,
14. <https://www.weforum.org/reports/schools-of-the-future-defining-new-models-of-education-for-the-fourth-industrial-revolution>
15. Canbek, M. Artificial Intelligence Leadership: Imitating Mintzberg's Managerial Roles. In Business Management and Communication Perspectives in Industry 4.0 IGI Global, pp. 173–187,2020.
16. Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P., & Dewhurst, M. A future that works: Automation, employment, and productivity. Chicago: McKinsey Global Institute.2017.
17. Haseski. H.I. What do Turkish pre-service teachers think about artificial intelligence? International Journal of Computer Science Education in Schools, 3(2), Doi: 10.21585/ijcses.v3i2.55,2019.

18. Geneva Gay, Preparing for culturally responsive teaching, *Journal of Teacher Education*, Vol. 53, No. 2, March/April pp 106-116, 2002.
19. Bartell T, Floden R., Richmond G, “What data and measures should inform teacher preparation? Reclaiming accountability. *Journal of Teacher Education*, 69(5), 426–428, 2018.
20. Marilyn Cochran-Smith, Emilie Mitescu Reagan, Centering Equity in Teacher Education Evaluation: From Principles to Transformative Enactment, *Journal of Teacher education*, Volume 73, Issue 5, 2022.
21. Alkin M., Christie C. “An evaluation theory tree”, In Alkin M. (Ed.), *Evaluation roots: Tracing theorists’ views and influences*, 2nd edition, pp. 91–112, SAGE, 2004.
22. Wogu, I. A. P., Misra, S., Olu-Owolabi, E. F., Assibong, P. A.. & Udoh, O. D. Artificial intelligence, artificial teachers and the fate of learners in the 21st century education sector: Implications for theory and practice. *International Journal of Pure and Applied Mathematics*, 119(16), pp. 2245–2259, 2018.